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Examining the effects of flood damage, federal hazard mitigation assistance, and flood insurance policy on population migration in the conterminous US between 2010 and 2019

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ABSTRACT

Flooding has significantly impacted the coastal communities in the US. However, few studies have examined the impacts of historical flood damages and hazard mitigation assistance (HMA) on community resilience. This research employs a Bayesian Hierarchical Model to investigate the effects of flood damage claims, flood insurance, HMA projects, and Small Business Assistance (SBA) loans on population migration between 2010 and 2019. Results indicate that historical flood damages and current hazard mitigation investments have significant negative effects on population migration, while flood insurance and CRS class have positive effects on community resilience. HMA projects from the federal government, including building acquisition, building elevation, building retrofit, planning-related projects, and infrastructure/utility projects, have negative effects on population migration. Nevertheless, SBA loans have significant positive group-level effects in metropolitans of Florida and Texas, both of which experienced devastating hurricanes between 2010 and 2019.

1. Introduction

Flooding has caused substantial damages and impacts to coastal built environments in the US and around the world (Gornitz et al., 2020). For example, from 1980 to 2020, over 76% of disaster events in the US are flooding related (National Centers for Environmental Information, 2022). Given the increasing frequency of climate extremes and the rapid growth of population in the flood-prone areas, flood risk is projected to increase over time (Wobus et al., 2021). The growing risk and exposure to flood-related disasters could result in population loss (Gray and Mueller, 2012).

To alleviate the negative impacts of flood disasters, adaptation plans and risk mitigation projects have been widely evaluated to reduce the community vulnerability (Brody and Highfield, 2005; Highfield and Brody, 2017; Noonan and Sadiq, 2019). In the US, the Federal Emergency Management Agency (FEMA) has implemented National Flood Insurance Program (NFIP) and Hazard Mitigation Assistance (HMA) grants to mitigate local flood risk (Kousky et al., 2018). FEMA also designed Community Rating System (CRS) to improve flood risk management (Noonan and Sadiq, 2019). Another important source of federal post-disaster aid is the Small Business Administration (SBA), which provides low interest disaster loans to businesses and households for post-disaster recovery.

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Community resilience has been defined as the ability of a system to prepare and withstand, absorb, and recover from adverse effects (IPCC, 2022). Although natural hazards and climate change have posed multi-causal social and economic pressures, changes of resilience in a community are largely reflected by population and economic changes (Noonan and Sadiq, 2019). Population loss in communities could be observed after natural disasters, and therefore, can reflect communities' capability of adapting to and ability of recovering from adverse effects (Cai et al., 2018; Qiang et al., 2017). Public risk mitigation projects play essential roles in mitigating natural disaster impacts. However, due to competing demands for many socially relevant resources, post-pandemic economic hardship, and unclear benefits of resilience investments, making consistent progress to build post-disaster resilience is challenging for decision-makers. Therefore, it is important to investigate whether FEMA's risk mitigation programs improved community resilience. This research aims to answers the following questions: How will historical flood damage and current HMA investment affect population migration across the conterminous US? Have federal-level risk mitigation programs and projects affected urban resilience and what are the effects at the local level?

2. Literature review

Previous research has examined the interactions between federal flood mitigation policies, government disaster aid, and flood insurance using panel data and longitudinal observations (Brody et al., 2012; Highfield and Brody, 2017; Kousky et al., 2018; Sadiq et al., 2019). For example, relying on fixed-effects (FE) model, Davlasheridze and Miao (2019) showed that public disaster assistance grants negatively affected flood insurance take-up rate at the county level, while individual assistance grants could increase the number of policyholders. Similarly, Noonan and Sadiq (2019) identified the negative effects of CRS on population change and housing development at the census tract level in the Gulf of Mexico. Sheldon and Zhan (2019) used a differences-in-differences approach to measure effects of natural hazards on home ownership rates, finding a 3–5 percentage decrease of home ownership in areas experiencing severe natural hazards.

To facilitate urban resilience, decision makers need to understand consequences of risk mitigation policies and projects. The multi-level model incorporates the dependences between samples from the same group, which could overcome the shortcoming of insufficient samples on individual levels. For example, Keenan et al. (2018) utilized a mixed linear model to evaluate climate gentrification on property price in Miami-Dade County, Florida. They divided counties into different jurisdiction groups and fitted random coefficients for each group. Ma et al. (2021) applied a multi-level logistic model to evaluate impacts of individuals' income inequality on the adoption of homeowner insurance and found income inequality impedes low-income homeowner insurance adoption but stimulates high-income homeowner insurance adoption.

In most existing studies, multi-level effects are often evaluated through a frequentist approach. Nevertheless, this approach may not work for sparse data. For example, the key assumption of variable independence in linear multilevel models could be violated given the high clustering effects between variables and may result in wrong parameter statistics (Nalborczyk et al., 2019). Bayesian hierarchical model (BHM) allows to simulate nested data across groups using Monte Carlo approach, and therefore, could reduce model parameter sensitivity to noise. Moreover, simulated results from BHM are usually more intuitive to interpret. Liu et al. (2008) applied BHM to predict air pollutants using four external driving factors. Based on a linear model structure, they utilized prior distributions of model parameters fitted from the conventional linear multilevel model. To improve the quantification of predictive uncertainty of regional frequency analysis, Renard (2011) proposed a two-level BHM to study the multivariate nonstationary frequency of hydrological variables. The first level of the model described the joint distribution of observations from means of an elliptical copula, and the second level included the spatial variability of parameters based on regression models. Another advantage of BHM is that the group-level effects from model outputs could provide spatial information by considering longitudinal observations. Chen et al. (2018) studied the empirical relationship between droughts and flood intensity and yield fluctuations of agriculture products using a BHM. Results indicated spatial patterns of drought and flood intensity on crop productions in China. Sairam et al. (2019) parameterized flood depth-damage functions using a hierarchical Bayesian approach and estimated flood loss estimation by accounting for the spatiotemporal heterogeneity in damage processes.

Climate change and natural disasters stimulate population displacement (Cattaneo et al., 2019). However, few studies have examined how federal risk mitigation programs and policies affect population migration in the US. The purpose of this study is to fill this research gap by integrating multiple sources of datasets to examine impacts of historical flood damage, HMA investments, flood insurance policy, and hazard mitigation programs on population migration in the conterminous US using a BHM approach. Our finding suggests that flood damages and HMA investments have negative effects on population migration. NFIP policy and CRS class positively effect population migrations. All examined HMA projects have negative effects on population migrations. This indicates insufficient risk mitigation assistance investments in improving community resilience during the study period. Nevertheless, SBA loans could have positive effects on population migration due to their prevalence after natural disasters.

Table 1
Statistical Summary of Variables.

Variable	Description	Mean	Minimum	Median	Maximum
Population migration	County-level net population migration from US Census	250.15	−79,758	−8	62,997
Household income	Median household income from the 5-year ACS dataset	54,708	23,251	52,650	1.46E5
Total Population	Total population from the 5-year ACS dataset	102,755	66	25,607	1E7
Unemployment	Number of unemployment from the 5-year ACS dataset	74,760	57	18,936.5	7.3E6
Population below poverty	Number of people below poverty from the 5-year ACS dataset	11,742	15	3895	9.23E5
Minority	Number of minorities from the 5-year ACS dataset	13.13	0	0	3480
Elderly people	Number of people with age greater than 65 from the 5-year ACS dataset	15,476	11	4697	1.18E6
NFIP policy count	Number of NFIP policy	1472	0	114	3.39E5
CRS class	Estimated CRS class of a county from the NFIP dataset	1.12	0	0	10
Flood damage claim count	Number of flood damage claims over the past three years	22.35	0	0	50,607
Total HMA investment	Total HMA project investment in the current year	4E5	0	0	8.83E8
Building acquisition project count	Number of building acquisition project over the past three years	0.05	0	0	24
Building elevation project count	Number of building elevation project over the past three years	0.02	0	0	23
Planning-related project count	Number of planning-related project over the past three years	0.07	0	0	6
Building retrofit project count	Number of building retrofit project over the past three years	0.01	0	0	6
Infrastructure/ Utility project count	Number of infrastructure/utility project over the past three years	0.03	0	0	12
SBA loan count	Number of SBA loans in the current year	0.84	0	0	1158

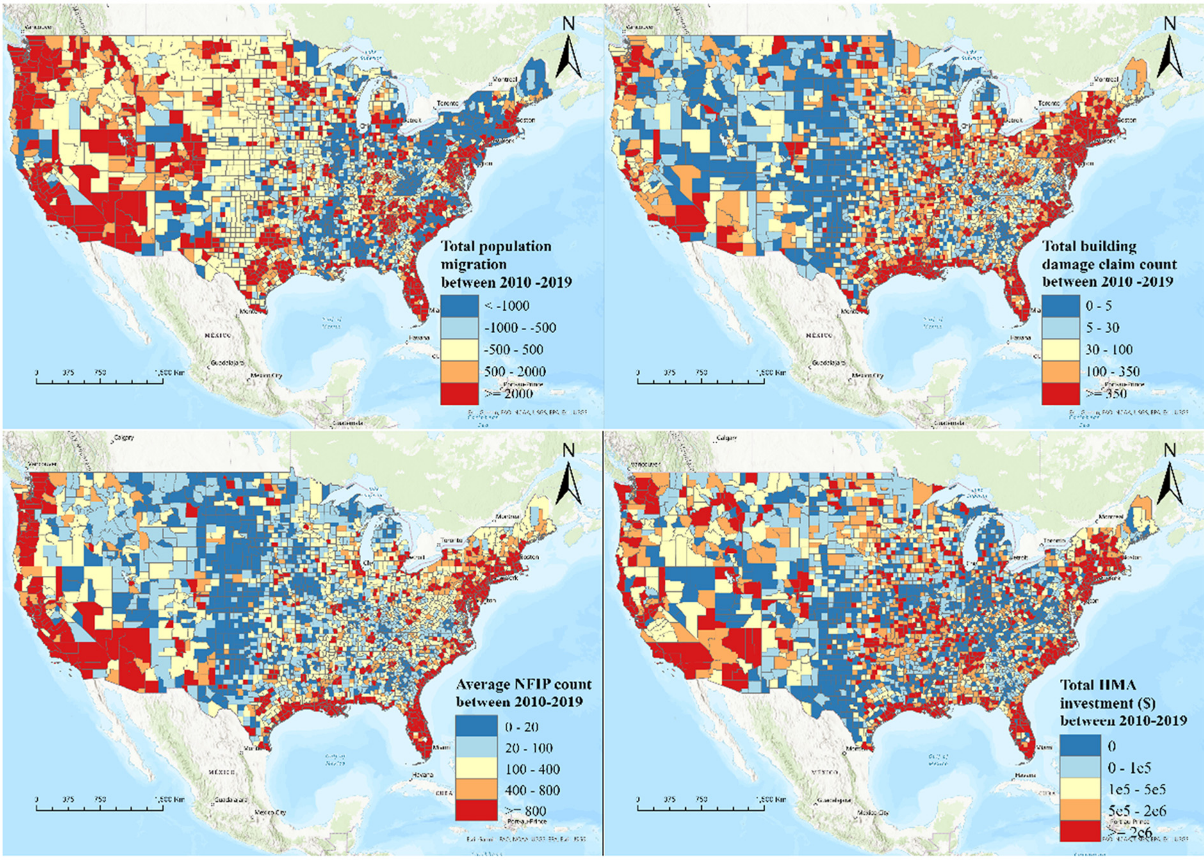

Fig. 1. The total population migration, total flood damage claim count, the average NFIP policy count, and the total HMA project investment at county-level between 2010 and 2019.

3. Materials and methods

3.1. Data and variables

We collected datasets in this study from multiple sources. First, the FEMA NFIP policy, flood damage claims, and FEMA HMA

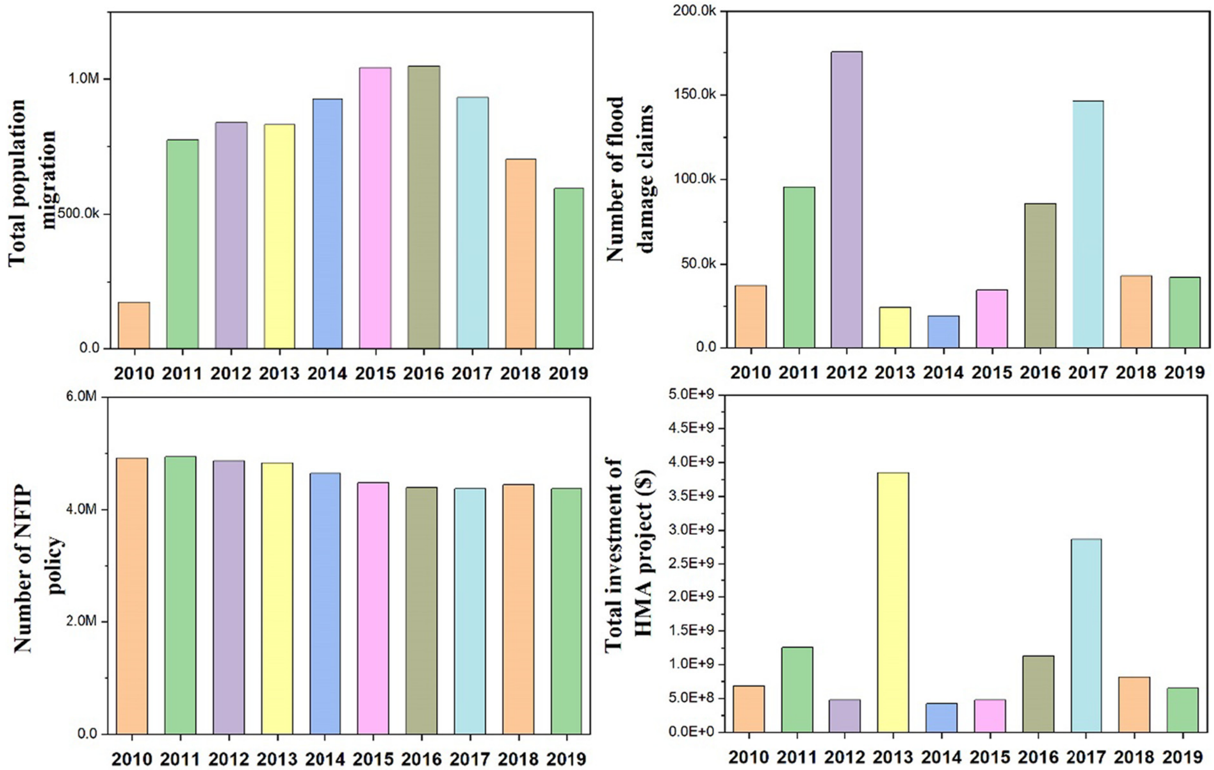

Fig. 2. National total population migration, total flood damage claim count, total NFIP policy count, and the total HMA project investment from 2010 to 2019.

project datasets were obtained from FEMA's Data website on fema.gov.[1] We collected SBA dataset from annual assistance report from SBA website.[2] Moreover, the county-level sociodemographic data was obtained from the 2014–2018 American Community Survey (ACS) 5-year estimates. The population migration data is from the US census bureau, which only covers 10 years county-level net population migration. Therefore, we chose the time frame between 2010 and 2019 in this research.

We aggregated FEMA's historical NFIP policy and flood damage claim datasets into county-level panel data. We estimated the annual NFIP policy count, the average CRS class, and the flood damage claim count of a county using the NFIP policy dataset and flood damage claim datasets. FEMA HMA projects contain information of hazard mitigation projects regarding hazard mitigation type, project type, number of projects, number of buildings, and total project cost. Given the prevalence of these projects in the HMA dataset during the study period, we selected building acquisition project, building elevation project, planning-related project, building retrofit project, infrastructure/utility project in this research. Due to low-frequency nature of flood hazards and corresponding hazard mitigation projects, we use the number of flood damage claims and the number of HMA projects over the past three years to measure historical impacts of flood damages and HMA projects on population migration (Davlasheridze and Miao, 2019). We also use the total HMA investment of a county from 2010 to 2019 to measure effects of current hazard mitigation investments on population migration.

The ACS dataset is conducted by the US Census Bureau over 5 years to represent detailed socioeconomic and demographic statistics of populations across the country. We chose median household income, total population, unemployment, the number of people below poverty, the number of minorities, and the number of elderly people to represent sociodemographic profile of a county. Statistical summary of model variables is shown in Table 1. We matched the above processed datasets using the five-digit Federal Information Processing Standards (FIPS) code, which uniquely identified a county in the US. However, HMA and SBA datasets contain incomplete location information for funded projects. We checked the FIPS code in these two datasets by hand to fill incomplete location information. To adjust all variables to the same scale in the modeling process, all variables are rescaled to the range 0 and 1.

We assume flood damage claims, the adoption of NFIP policy, and the allocation of HMA projects and SBA projects vary in different metropolitan regions due to spatial variations of physical vulnerability and local public adaptation efforts. Therefore, we measure group-level effects by defining a collection of counties in the neighborhood as communities (Sadiq et al., 2019). U.S. Core Based Statistical Areas (CBSA) defines the metropolitan or micropolitan regions to represent a core urban area with a high degree of social and economic integration of populations nucleus. A CBSA consists of at least a US county, or a collection of counties associated with at

[1] FEMA datasets have been retrieved from the OpenFEMA website: https://www.fema.gov/about/openfema/data-sets.
[2] SBA datasets have been retrieved from SBA website: https://www.sba.gov/funding-programs/disaster-assistance.

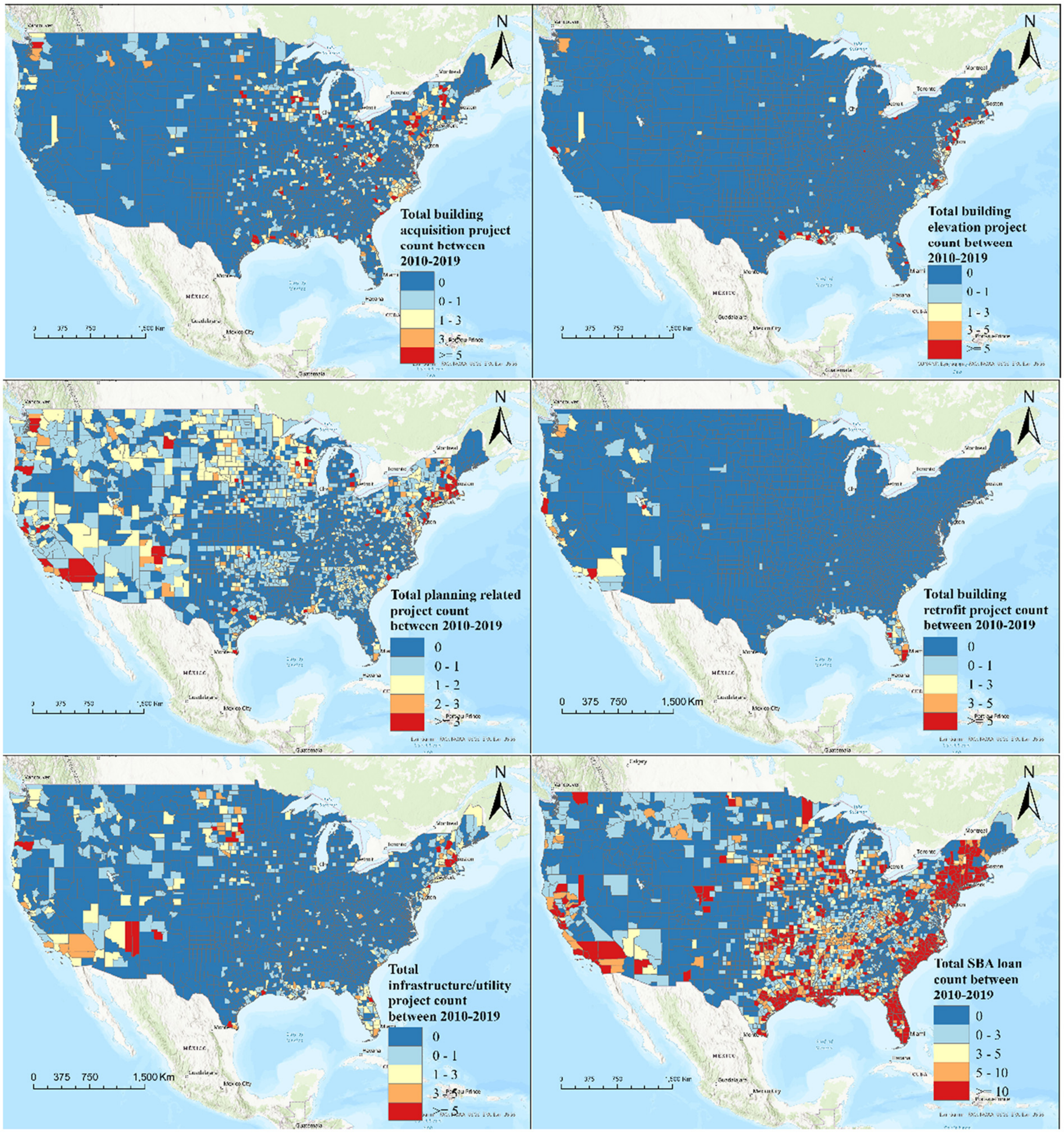

Fig. 3. Total building acquisition project count, building elevation project count, wind retrofit project count, and SBA project count between 2010 and 2019.

least one Metropolitan or Micropolitan with the population of at least 10,000. In this research, we use CBSA to determine group-level effects of variables.

3.2. Bayesian hierarchical model

Multi-level models offer the flexibility to handle dependency between observations from the same group by partitioning the total variance of datasets into variation due to groups and individuals. As a result, there are group-level and population-level estimates. Group-level estimates vary between groups, while population-level estimates are constant across the whole sample. In hierarchical Bayesian models, the entire posterior distribution of parameter values can be estimated based on prior distribution and likelihoods function of the dataset. Group level variations could be estimated to inform generalizability of the results. Population migrations are

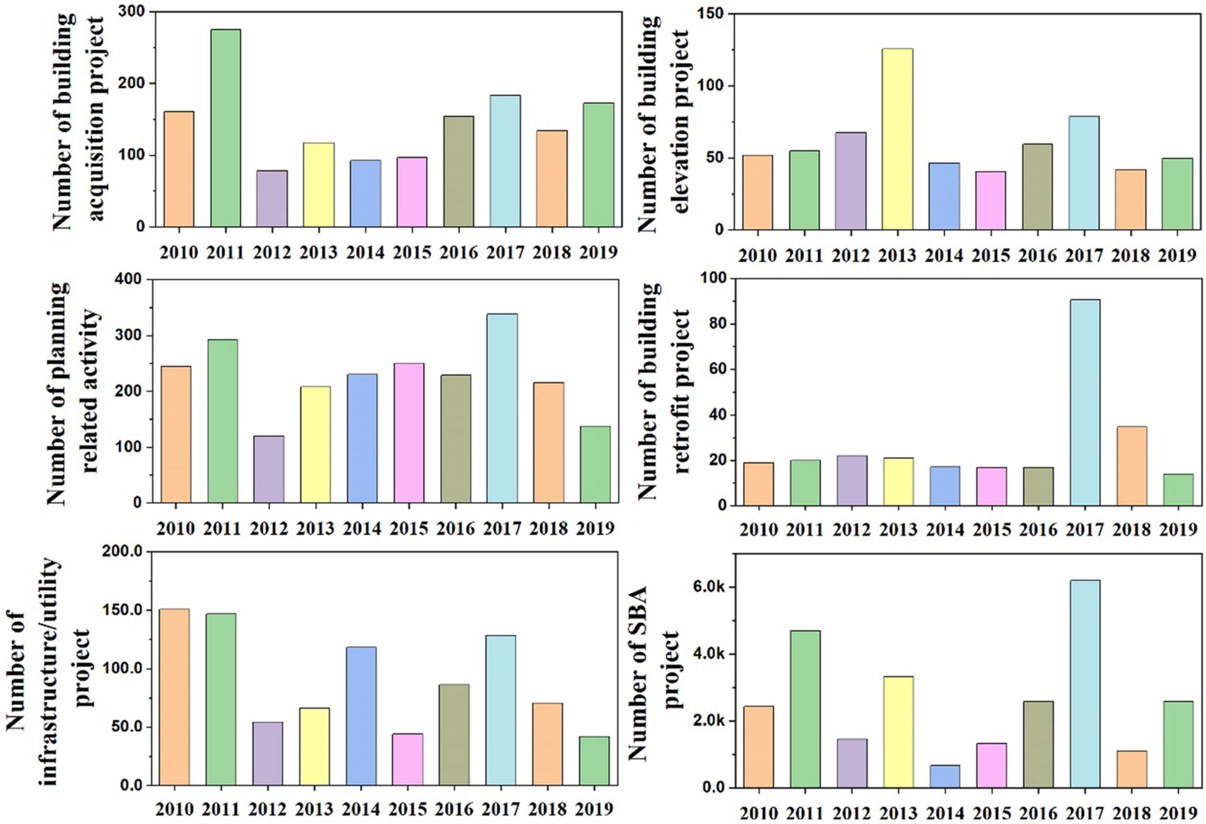

Fig. 4. Aggregated total building acquisition project count, building elevation project count, wind retrofit project count, and SBA project count from 2010 to 2019.

Table 2
Population-level effects of parameters.

Variables	Mean	Standard error	2.5% Quantile	97.5% Quantile
Intercept	−0.01	0.018	−0.046	0.026
Median household income	0.187	0.014	0.161	0.213
Total Population	7.749	0.226	7.319	8.198
Unemployment	−6.046	0.23	−6.508	−5.597
Population below poverty	−0.632	0.056	−0.741	−0.522
Minority	−0.777	0.022	−0.817	−0.734
Elderly people	−0.454	0.056	−0.566	−0.345
NFIP policy count	0.195	0.009	0.178	0.213
CRS class	0.048	0.01	0.029	0.067
Flood damage claim count	−0.054	0.005	−0.064	−0.044
Total HMA investment	−0.057	0.006	−0.068	−0.045
Acquisition project count	−0.028	0.008	−0.044	−0.013
Building elevation project count	−0.034	0.008	−0.051	−0.018
Planning-related project count	−0.009	0.005	−0.019	0.001
Building retrofit project count	−0.106	0.009	−0.122	−0.089
Infrastructure/Utility project count	−0.004	0.007	−0.018	0.01
SBA loan count	0.062	0.006	0.05	0.074

estimated through Bayesian inference based on partial pooling of variables in the same metropolitan or micropolitan region. Therefore, both population-level and group level parameter effects could be estimated. In the hierarchical model setting, assuming the response variable y could be predicted through a linear combination (μ) of predictors, then the response y has a distribution D, with $y \sim D(\mu, \boldsymbol{\theta})$. μ can be expressed as.

We also account for sociodemographic attributes in the model. County-level median household income, total population, number of unemployed people, the number of people below poverty, the number of minorities, and the number of elderly people are selected to reflect a county’s socioeconomic profile.

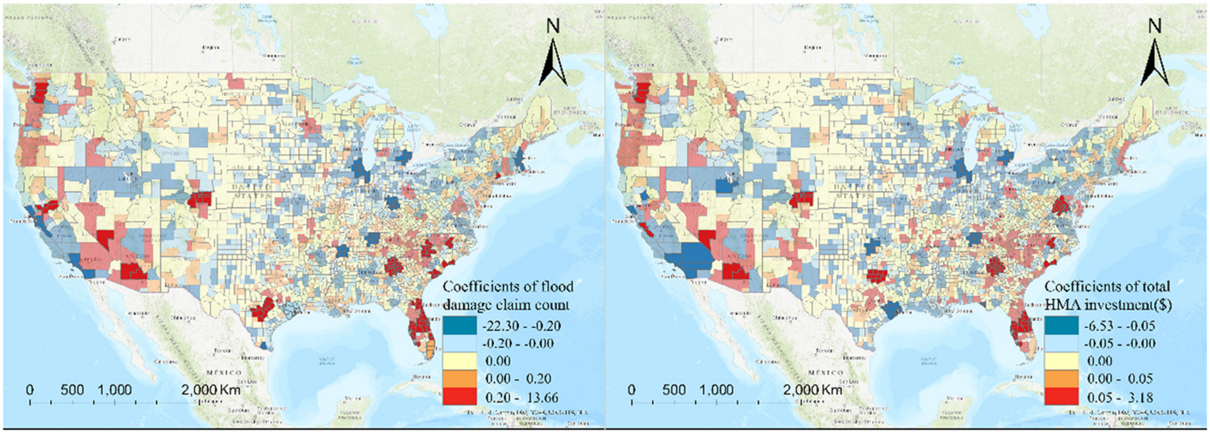

Fig. 5. Posterior group-level coefficients of damage claim count and HMA investments between 2010 and 2019. Note: transparent areas have inconsistent positive or negative group-level effects within 95% quantile of the parameter distribution.

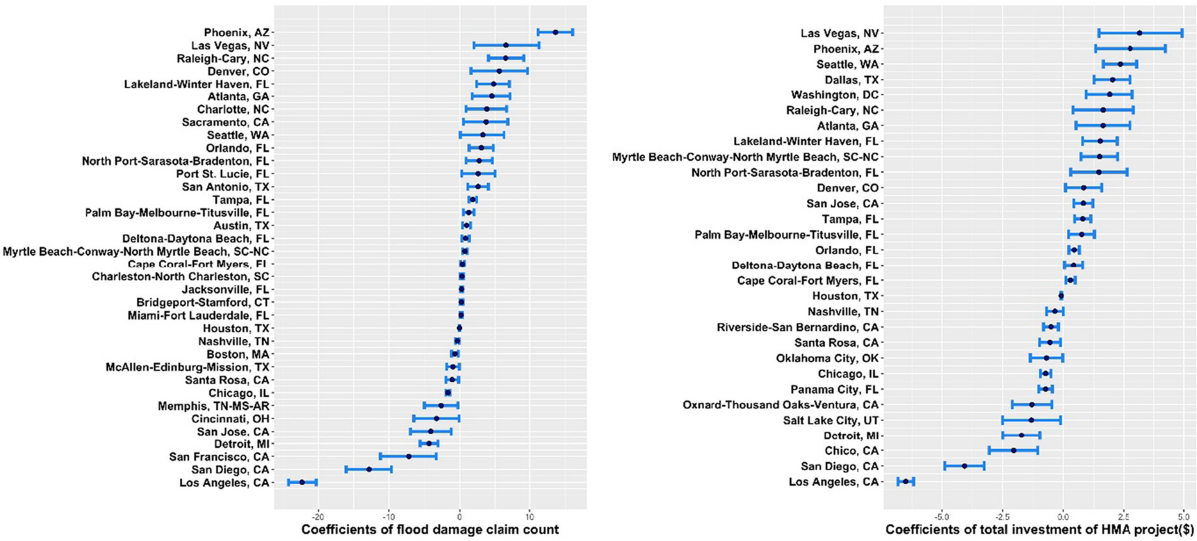

Fig. 6. US Metropolitans/Micropolitan with consistent group level effects of damage claim count and total HMA investments.

$$\mu = X\beta + Z\alpha + \epsilon$$

In above equation, β and α are corresponding coefficients at the population-level and group level. β and α are assumed to have a multivariate normal distribution. $\boldsymbol{X}$ is the matrix of population-level factors, including all variables in Table 1. $\boldsymbol{Z}$ is group-level factor matrix. To measure group-level effects of multiple variables, we built separate models to estimate their group level effects on population migration individually. There group-level variables include flood damage claim count, HMA investment, NFIP policy count, the average CRS class, building acquisition project count, building elevation project count, planning-related project, building retrofit project count, infrastructure/utility project, and SBA loan count. $\epsilon \sim N(0, \tau^2)$ is the residual of the intercept. To avoid noninformative prior in the parameter estimation process, the prior distributions of BHM parameters were estimated from a linear mixed effects model from R software.

4. Results

4.1. Summary of variables

We processed multi-source datasets into county-level longitudinal observations. Fig. 1 shows county-level total population migration, building damage claim count, NFIP policy count, and total HMA project investment between 2010 and 2019. The population migration results showed that coastal areas have faster population growth. Dramatic population growths usually occurred

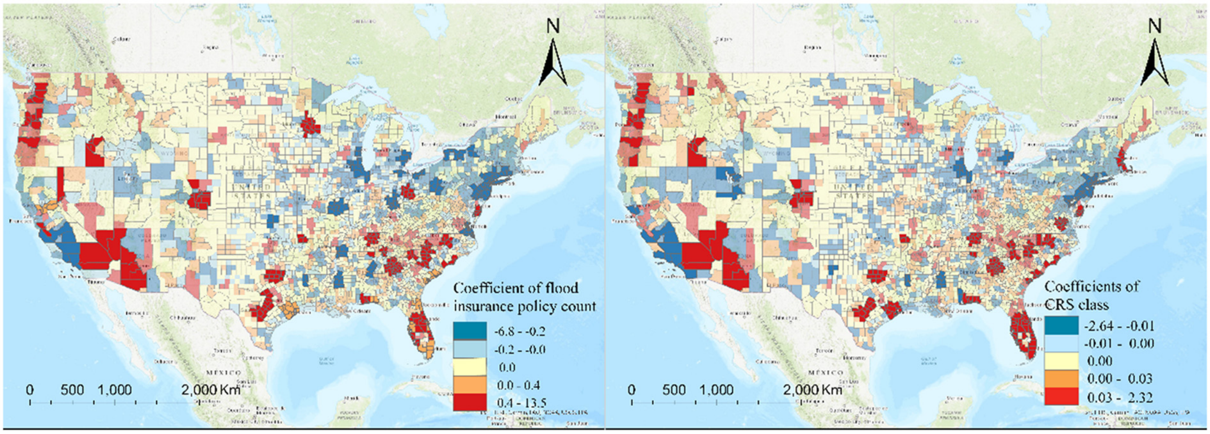

Fig. 7. Posterior group-level coefficients for NFIP policy and CRS class. Note: transparent areas have inconsistent positive or negative group-level effects within 95% quantile of the parameter distribution.

around large metropolitan areas, such as Southeast Florida, Houston, San Francisco, and Los Angeles. In addition, there were more population migrations in the south compared to the north (Fig. 1). Nevertheless, flood damage claims were more in coastal cities of the northeast and the south. Northeast metropolitan areas, such as Boston, New York, and Washington, had more flood damage claims. Coastal counties in the south experienced more flood damages as well, such as Houston, New Orleans, and Miami-Ford Lauderdale. These results are consistent with historical Hurricane records. For example, in October 2012, Hurricane Sandy with category 3 landed in northern New Jersey, Hurricane Harvey, a category 4 hurricane, impacted Texas and Louisiana in August 2017, and Hurricane Irma caused widespread destructions in Southeast Florida in September 2017. All these hurricanes brought tremendous losses to local communities. The adoption of flood insurance had a similar pattern to flood damage claims. However, although coastal counties on the west side of the US have not experienced large damage claims over the past decade, they have large numbers of flood insurance policyholders. Fig. 1 also shows the total HMA project investments between 2010 and 2019. The HMA investments were higher in coastal states and counties along the Mississippi River. For example, New Orleans, the ends of Mississippi River, and coastal counties along the Atlantic Ocean and Pacific Ocean received more HMA investments.

Fig. 2 shows national total population migration, total flood damage claims, total flood insurance policies, and total HMA investments from 2010 to 2019. The population migration in 2016 was the highest over the past decade, while it was much lower in 2010 compared to other years. Flood damage claim counts in 2012 and 2017 were significantly higher than in other years due to two catastrophic disasters. The total adoption of flood insurance ranged between 4.5 million and 5 million. Compared to the total flood damage claim counts, the total number of HMA projects was high in 2013 and 2017, which indicated higher federal post-disaster assistance was invested after Hurricane disasters.

We use Fig. 3 and Fig. 4 to show six kinds of hazard mitigation assistance projects from the HMA dataset and SBA dataset between 2010 and 2019. They are building acquisition project counts, building elevation project counts, planning-related project count, building retrofit project count, infrastructure/utility project count, and SBA loan counts. Fig. 3 shows the total number of each kind of project at the county-level.

Most building acquisition projects are on the east side of the US. Building elevation projects are more located along coastal areas experienced high flood damages. New Jersey, Texas, and Louisiana have more building elevation projects. However, Southeast Florida, one of the most vulnerable regions with high flood damage claims between 2010 and 2019, have few federal supported building acquisition projects and building elevation projects. Many planning-related projects are funded in vulnerable areas, such as counties in the northeast, southeast, and the Gulf of Mexico. In addition, counties in the west and north also received some planning-related projects. Building retrofit projects are more in the southeast of Florida and west coast. The number of infrastructure/utility projects is higher in northeast and southeast of the US. The number of SBA loans is high in vulnerable regions, such as coastal counties of New Jersey, North Carolina, Florida, and Gulf Coast of the United States, as well as areas experienced high flood damage claims. Fig. 4 shows that the number of building acquisitions is the highest in 2011 and the lowest in 2012. However, after 2015, the number of building acquisition project increased gradually. Building elevation projects are more in 2012, 2013, 2016, and 2017, which are consistent with the appearance of Hurricane disasters. The number of planning-related project ranged between 100 and 300, and was higher after Hurricane disasters. The number of building retrofit project increased sharply in 2017. The number of infrastructure/utility projects were much less than the number of planning-related projects but increased after a hurricane disaster appeared within 3 years. SBA project count was the highest in2013 and 2017, which means more SBA projects were funded to local households after Hurricane Harvey.

4.2. Population-level effects

The baseline results are presented in Table 2. We use Markov chain Monte Carlo algorithms with 3 chains to train posterior

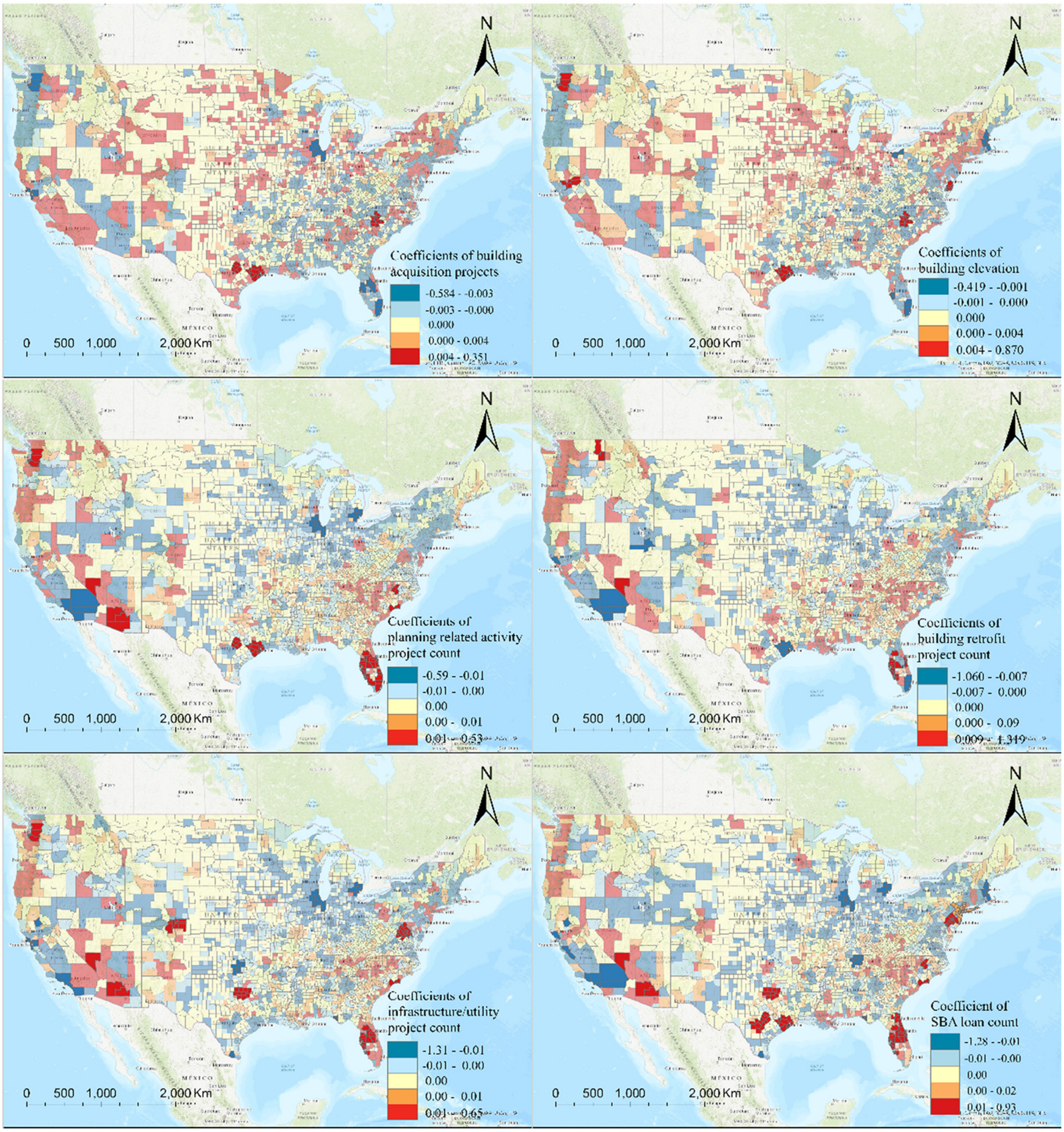

Fig. 8. Posterior group level coefficients of HMA projects and SBA projects. Note: transparent areas have inconsistent positive or negative group-level effects within 95% quantile of the parameter distribution.

distribution of model parameters and results indicate all parameters are converged. Population-level effects of sociodemographic variables are shown in row 2 to row 7. Median household income and total population have positive effects for population migration. Unemployment, population below poverty, minority, and the elderly people, all have negative effects on population migration. These variables do not change in the study period and coefficients are significant within the 95% quantile of their distributions.

The number of NFIP policy and the CRS class are positive and significant predictors on population migration. These results mean that more population will flow into areas with higher NFIP policies and CRS class, which are large metropolitans in coastal areas of the south or on west sides of the US. The distributions of coefficient of flood damage claim count and total HMA investment are consistent negative within the 95% quantile. Consequently, more population will migrate out of areas experienced with flood damages. Moreover, HMA projects are more likely to be post-disaster assistances rather than pre-disaster mitigation.

The five kinds of HMA project all have negative effects on population migration. The number of building acquisition projects, the

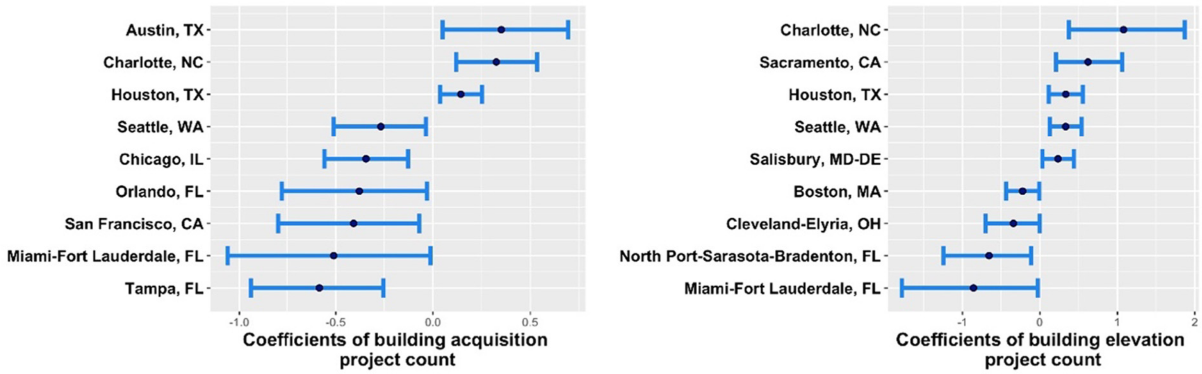

Fig. 9. Metropolitans/Micropolitan with consistent group-level effects of building acquisition projects and building elevation projects within the 95% quantile of parameter distributions.

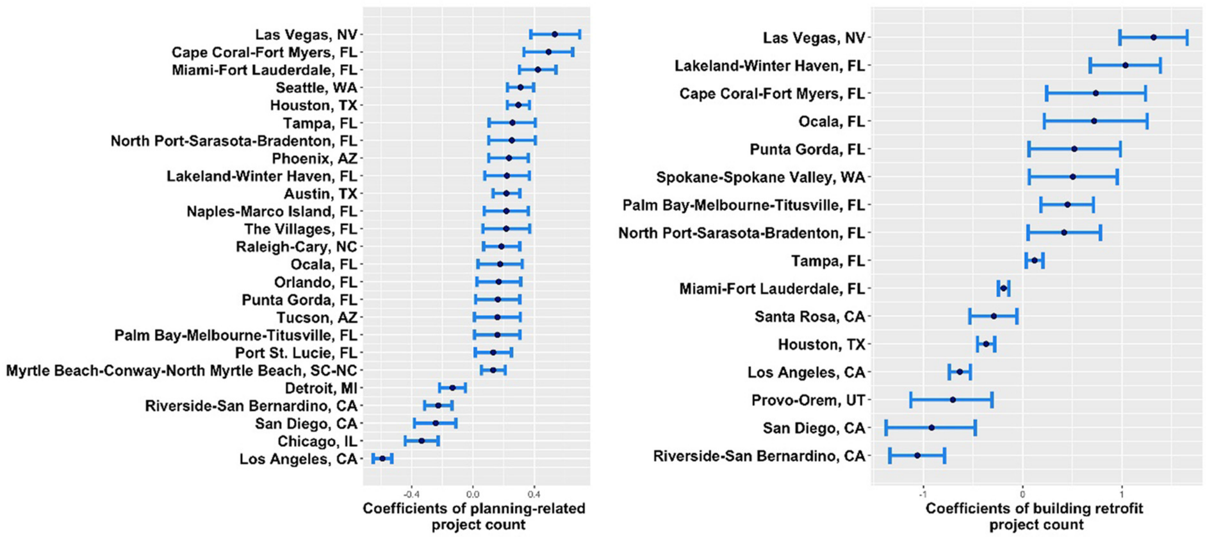

Fig. 10. Metropolitans/Micropolitan with consistent group level effects of planning-related projects and building retrofit projects within the 95% quantile of parameter distributions.

number of building elevation project, and the number of building retrofit project all have negative and significant effects on population migration. The number of planning-related project and the number of infrastructure/utility project have less impacts on population migration compared to other kinds of HMA projects and parameter distributions of these two variables varies between −0.02 and 0.01. On the other hand, the SBA loan count have positive effects on population migration. This result indicates higher SBA loans in an area will increase more people to the area.

Above results indicate that either the number of SBA loans or the number of NFIP policy has positive effects on population growth, while a higher number of HMA projects usually indicates population loss. To further evaluate local effects of these variables on population migration, we ran multiple BHMs to measure group-level effects of these variables individually by only treating demographical variables as population-level variables.

4.3. Group-level effects

Fig. 5 shows posterior group-level effects of flood damage claims and HMA investment on the spatial scale. Group-level effects of flood damage claims count and HMA investment have similar patterns on the spatial scale, which illustrate the fact that most HMA investments are post-disaster assistance. To better visualize significant group-level effects on the spatial scale, we treat areas with inconsistent positive or negative group-level effects within the 95% quantile more transparent. Metropolitans in Florida, such as Miami-Ford Lauderdale and Tampa, have consistent positive effects of flood damage claims and HMA investments. Nevertheless, flood damage claims and HMA investments have consistent negative effects in metropolitan areas of the west US, such as Houston and San Francisco. Although group-level effects of flood damage claims and HMA investments in New York are positive, they are not consistent

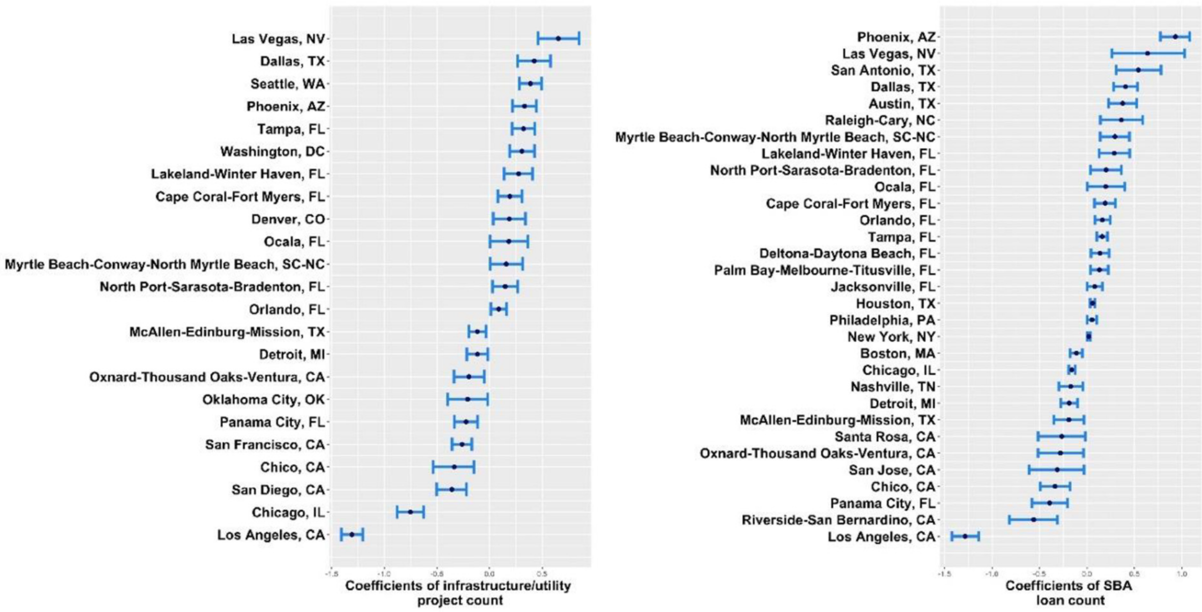

Fig. 11. Metropolitans/Micropolitan with consistent group level effects of infrastructure/utility projects and SBA projects within the 95% quantile of parameter distributions.

within the 95% confidence interval. Fig. 6 shows all metropolitan or micropolitan areas with consistent positive or negative coefficients of flood damage claim count and total HMA investment. Las Vegas, Phoenix, and Raleigh-Cary have high positive effects of flood damage claim count and total HMA investment, while Detroit, San Diego, and Los Angeles have high negative effects.

Group-level effects of NFIP policy and CRS class are shown in Fig. 7. NFIP policy and CRS class have similar spatial patterns on average. Coastal metropolitan regions in the south coast, such as Miami-Fort Lauderdale and Houston, have consistent positive group-level effects for population migration within the 95% quantile of parameter distributions. Metropolitans in the northeast, such as New York, have consistent negative group-level effects for both NFIP policy and CRS class. It indicates population may decrease after Hurricane Sandy. Metropolitan areas in the northwest US show positive group-level effects for population migration. Nevertheless, coastal metropolitans in the southwest US are more likely to have negative group-level effects for population migration.

Fig. 8 show group-level effects of multiple HMA projects. Six group-level variables, including the numbers of building acquisition project, building elevation project, planning-related project, building retrofit project, infrastructure/utility project, and SBA loans, were examined individually to examine their group-level effects on metropolitan or micropolitan regions. Fig. 9, Fig. 10, and Fig. 11 show Metropolitans/Micropolitan areas with consistent group level effects of HMA projects and SBA projects within the 95% quantile of parameter distributions.

Building acquisition projects have a consistent positive effect on population migration in Houston, Charlotte, and Austin, but coefficients of building acquisition projects are consistent negative for metropolitan regions like San Francisco and Miami-Ford Lauderdale. Building elevation project has consistent positive effects in Houston but is opposite in southeast Florida. In New York, both building acquisition project and building elevation project have inconsistent group-level effects for population migration. These effects are negative for building acquisition and positive for building elevation. Planning-related project has consistent positive effects in both Houston, Austin, and coastal areas of Florida. However, building retrofit project has consistent negative effects in Houston and Miami-Ford Lauderdale. In general, building-level risk mitigation assistances decreased population migration in Southeast Florida but varied in Texas and New Jersey.

On the other side, coefficients of infrastructure/utility project are positive in many Florida coastal counties but are not significant in New York, Miami-Ford Lauderdale, and Houston. It is possible that these projects are invested after natural disasters. The SBA loan counts have more significant group-level effects on population migration. SBA loans have positive effects in metropolitans of Texas and Florida. Besides counties in Southeast Florida, other counties in Florida have positive coefficients for SBA loans. Miami-Ford Lauderdale has inconsistent group-level coefficients for SBA projects within the 95% confidence interval. This indicates SBA projects have not substantially improved community resilience after natural disasters in Southeast Florida.

4.4. Sensitivity of group-level effects

Since population migration could measure resilience of a metropolitan on the population scale, we fitted linear models with 95% confidence interval to measure sensitivity of group-level coefficients of variables on population migration. These variables include flood damage claims, HMA investment, HMA projects, and SBA loans. Results are shown in Fig. 12 and Fig. 13. Flood damage claims,

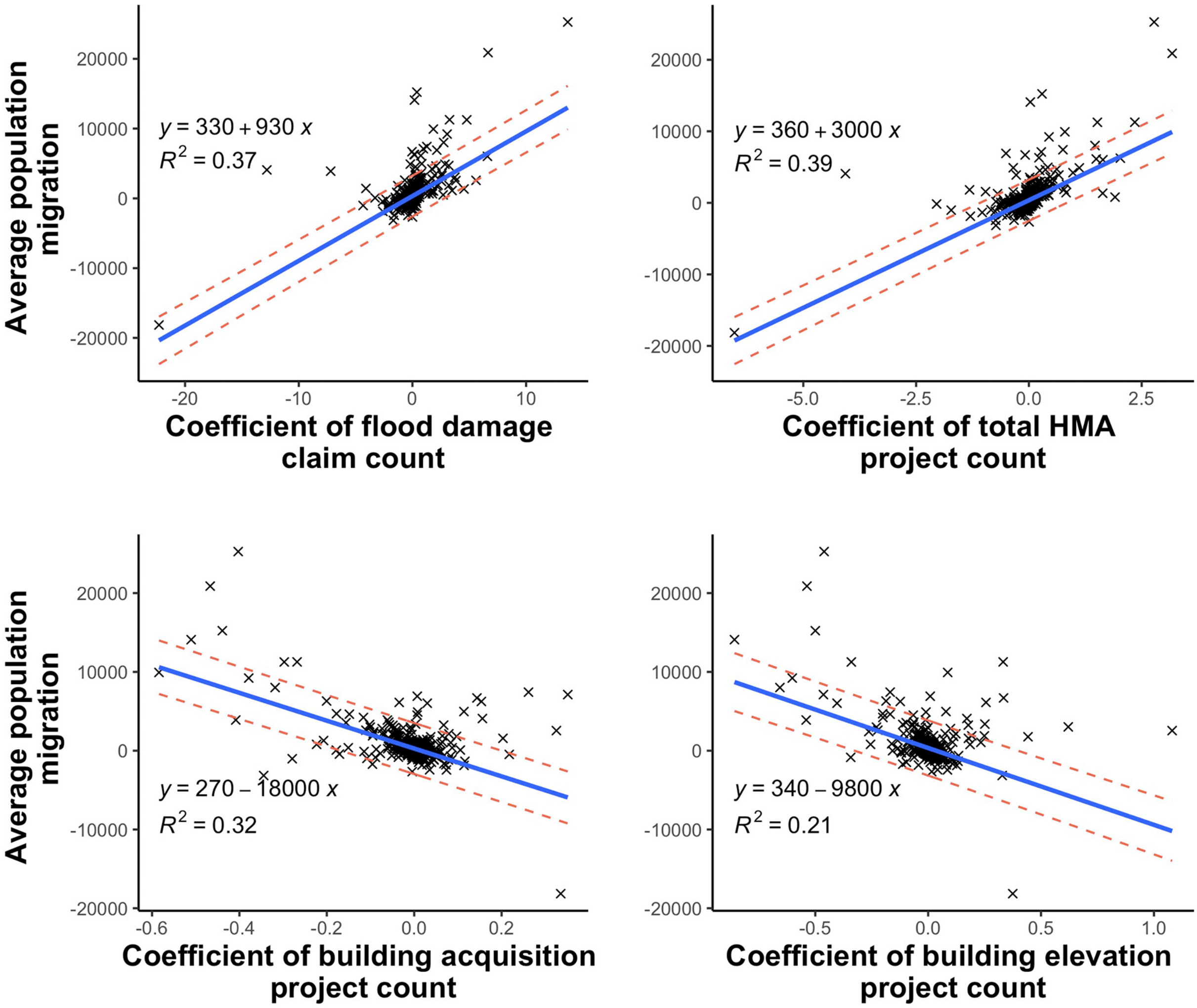

Fig. 12. Relationship between population migration and flood damage, HMA investment, and HMA project.

HMA investments, building acquisition project, building elevation project, and building retrofit project all have significant but weak linear relationship with population migration. Among these variables, population migration has negative impacts on coefficients of building acquisition project and building elevation project but has positive impacts on other coefficients. This indicates that building acquisition projects and building elevation projects are not invested more in areas with high population inflows, while flood damage and HMA projects are likely to be invested more in areas with high population inflows. Moreover, high flood damages also associate with high population inflows in the US. Population migration has positive impacts on coefficients of planning-related project, infrastructure/utility project, and SBA loan count. These fitted linear models have relative high accuracy. This shows planning-related projects, infrastructure/utility project, and SBA loans are more in high population growth areas.

5. Conclusions

Coastal and riverine flooding could trigger destructive consequences to urban areas. However, given the low frequency of natural hazards, it is difficult to measure how existing risk mitigation policy and hazard mitigation assistance affect community resilience. On the federal level, a better understanding of the performance of existing risk mitigation policy and hazard mitigation assistance could help design more effective risk mitigation policies. This study treats population migration as the metric to measure community resilience and applies a Bayesian multi-level model with data collected from multiple sources between 2010 and 2019. Compared to existing FE model, our methodology could effectively capture population-level and group-level effects of variables and provide intuitive results for interpretation. Compared to spatial data analysis approaches, the BHM applied in this study could avoid the issue of data sparsity on the spatiotemporal scales (Qiang et al., 2017).

Between 2010 and 2019, three catastrophic hurricanes have happened in the northeast southeast, and the south coast of the country. It could be observed that flood damages could decrease community resilience. Although in some metropolitan areas, such as

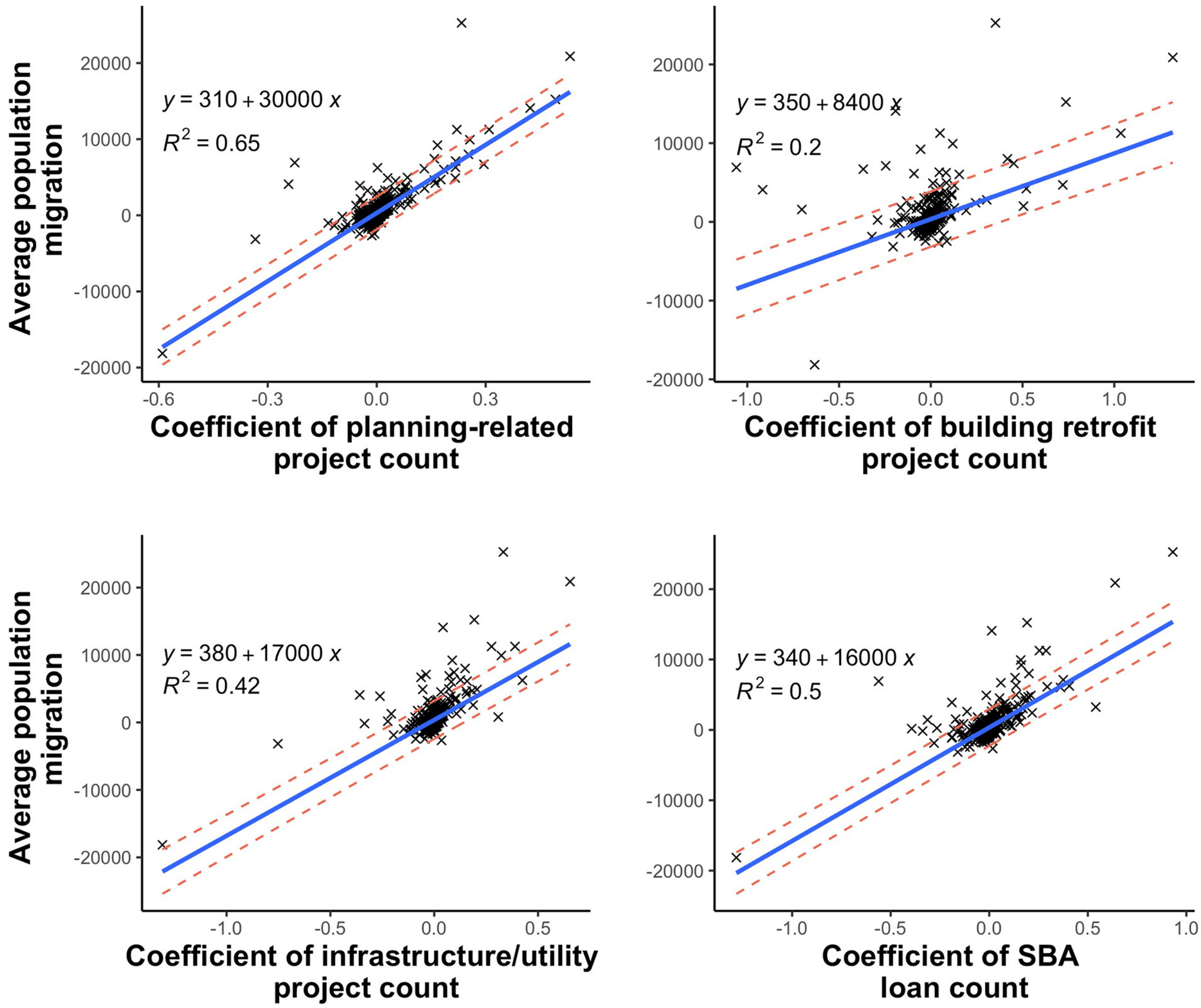

Fig. 13. Relationship between population migration and HMA projects and SBA loans.

New York, the group-level effects of NFIP policy and CRS class are negative, they play positive effects on community resilience on the population scale. These results also support finding in existing research, where participating CRS could promote flood management decision-making and reduce damages (Highfield and Brody, 2017; Tyler et al., 2021). HMA projects, including building acquisition, building elevation, planning-related projects, building retrofit, and infrastructure/utility projects, all have negative population effects on community resilience. However, sensitivity results indicate that when planning-related projects, building retrofit projects, and infrastructure/utility projects are more funded in highly vulnerable areas, they could also improve community resilience. SBA project, as an important source of post-disaster recovery, could increase community resilience. From above results, we suggest more HMA projects should be allocated to areas that are highly susceptible to flood damages, such as Miami-Ford Lauderdale and New York. Between 2019 and 2019, Building acquisition, elevation, and retrofit projects all had negative effects in Miami-Ford Lauderdale area. Correspondingly, these areas received zero building acquisition and building elevation assistance projects, and only Miami County and Broward County received a few building retrofit projects after Hurricane Irma. Insufficient amount of HMA projects after natural disasters decreases community resilience of these areas.

Results of this study have shown that flood damages, federal flood insurance policy, and investments in hazard mitigation assistance could affect population migration under the uncertain flood disasters. Nevertheless, this study also has some limitations. First, FEMA's HMA program dataset contains multiple kinds of hazard mitigation projects. We use total HMA investment and five kinds of major hazard mitigation projects to measure effects of HMA projects on population migration in this study. There are also multiple programs in the HMA dataset, namely Hazard Mitigation Grant Program (HMGP), Flood Mitigation Assistance (FMA) grant program, and Pre-Disaster Mitigation (PDM) grant program. We did not distinguish these programs in our analysis, which could be further explored. Second, this study collects data from multiple sources. Nevertheless, we did not include other variables, such as ecological indicators, in this study. Future studies would incorporate more ecological indicators into the analysis (Brody et al., 2015; Brody et al., 2012). Third, although population change is an important metric to measure community resilience from the population scale, multiple other variables, such as housing development, could also represent community resilience (Noonan and Sadiq, 2019). In future studies, a resilience index developed by multiple socioeconomic variables could be used to measure relationship between federal risk mitigation assistance on community resilience.

CRediT authorship contribution statement

Yu Han: Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Xinyue Ye:** Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

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References

Brody, S.D., Highfield, W.E., 2005. Does planning work?: testing the implementation of local environmental planning in Florida. J. Am. Plan. Assoc. 71 (2), 159–175. https://doi.org/10.1080/01944360508976690.

Brody, S.D., Peacock, W.G., Gunn, J., 2012. Ecological indicators of flood risk along the Gulf of Mexico. Ecol. Indic. 18, 493–500. https://doi.org/10.1016/j.ecolind.2012.01.004.

Brody, S.D., Highfield, W.E., Blessing, R., 2015. An analysis of the effects of land use and land cover on flood losses along the Gulf of Mexico coast from 1999 to 2009. JAWRA J. Am. Water Res. Ass. 51 (6), 1556–1567. https://doi.org/10.1111/1752-1688.12331.

Cai, H., Lam, N.S.N., Zou, L., Qiang, Y., 2018. Modeling the dynamics of community resilience to coastal hazards using a Bayesian network. Annals. Am. Ass. Geograph. 108 (5), 1260–1279. https://doi.org/10.1080/24694452.2017.1421896.

Cattaneo, C., Beine, M., Fröhlich, C.J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M.,…Schraven, B., 2019. Human migration in the era of climate change. Rev. Environ. Econ. Policy 13 (2), 189–206. https://doi.org/10.1093/reep/rez008.

Chen, H., Liang, Z., Liu, Y., Jiang, Q., Xie, S., 2018. Effects of drought and flood on crop production in China across 1949–2015: spatial heterogeneity analysis with Bayesian hierarchical modeling. Nat. Hazards 92 (1), 525–541. https://doi.org/10.1007/s11069-018-3216-0.

Davlasheridze, M., Miao, Q., 2019. Does governmental assistance affect private decisions to insure? An empirical analysis of flood insurance purchases. Land Econ. 95 (1), 124–145. https://doi.org/10.3368/le.95.1.124.

Gornitz, V., Oppenheimer, M., Kopp, R., Horton, R., Orton, P., Rosenzweig, C.,…Patrick, L., 2020. Enhancing new York City's resilience to sea level rise and increased coastal flooding. Urban Clim. 33, 100654 https://doi.org/10.1016/j.uclim.2020.100654.

Gray, C.L., Mueller, V., 2012. Natural disasters and population mobility in Bangladesh. Proc. Natl. Acad. Sci. 109 (16), 6000–6005. https://doi.org/10.1073/pnas.1115944109.

Highfield, W.E., Brody, S.D., 2017. Determining the effects of the FEMA Community rating system program on flood losses in the United States. Internat. J. Dis. Risk Red. 21, 396–404. https://doi.org/10.1016/j.ijdrr.2017.01.013.

IPCC, 2022. In: Pörtner, H.O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., Rama, B. (Eds.), Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. *Cambridge University Press. In Press*.

Keenan, J.M., Hill, T., Gumber, A., 2018. Climate gentrification: from theory to empiricism in Miami-Dade County, Florida. Environ. Res. Lett. 13 (5), 054001 https://doi.org/10.1088/1748-9326/aabb32.

Kousky, C., Michel-Kerjan, E.O., Raschky, P.A., 2018. Does federal disaster assistance crowd out flood insurance? J. Environ. Econ. Manag. 87, 150–164. https://doi.org/10.1016/j.jeem.2017.05.010.

Liu, Y., Guo, H., Mao, G., Yang, P., 2008. A Bayesian hierarchical model for urban air quality prediction under uncertainty. Atmos. Environ. 42 (36), 8464–8469. https://doi.org/10.1016/j.atmosenv.2008.08.018.

Ma, C., Baker, A.C., Smith, T.E., 2021. How income inequality influenced personal decisions on disaster preparedness: a multilevel analysis of homeowners insurance among hurricane Maria victims in Puerto Rico. Internat. J. Dis. Risk Red. 53, 101953 https://doi.org/10.1016/j.ijdrr.2020.101953.

Nalborczyk, L., Batailler, C., Lœvenbruck, H., Vilain, A., Bürkner, P.C., 2019. An introduction to Bayesian multilevel models using brms: a case study of gender effects on vowel variability in standard Indonesian. J Speech Lang Hear Res. 62 (5), 1225–1242. https://doi.org/10.1044/2018_jslhr-s-18-0006.

National Centers for Environmental Information, . U.S. Billion-Dollar Weather and Climate Disasters. *https://www.ncei.noaa.gov/access/billions/*. https://doi.org/10.25921/stkw-7w73.

Noonan, D.S., Sadiq, A.-A., 2019. Community-scale flood risk management: effects of a voluntary National Program on migration and development. Ecol. Econ. 157, 92–99. https://doi.org/10.1016/j.ecolecon.2018.11.005.

Qiang, Y., Lam, N.S.N., Cai, H., Zou, L., 2017. Changes in exposure to flood hazards in the United States. Annals Am. Ass. Geograph. 107 (6), 1332–1350. https://doi.org/10.1080/24694452.2017.1320214.

Renard, B., 2011. A Bayesian hierarchical approach to regional frequency analysis. Nat. Hazards 47 (11). https://doi.org/10.1029/2010WR010089.

Sadiq, A.-A., Tyler, J., Noonan, D.S., 2019. A review of community flood risk management studies in the United States. Internat. J. Dis. Risk Red. 41, 101327 https://doi.org/10.1016/j.ijdrr.2019.101327.

Sairam, N., Schröter, K., Rözer, V., Merz, B., Kreibich, H., 2019. Hierarchical Bayesian approach for modeling spatiotemporal variability in flood damage processes. Water Resour. Res. 55 (10), 8223–8237. https://doi.org/10.1029/2019WR025068.

Sheldon, T.L., Zhan, C., 2019. The impact of natural disasters on US home ownership. J. Assoc. Environ. Resour. Econ. 6, 1169–1203.
Tyler, J., Sadiq, A.-A., Noonan, D.S., Entress, R.M., 2021. Decision making for managing community flood risks: perspectives of United States floodplain managers. Internat. J. Dis. Risk Sci. 12 (5), 649–660. https://doi.org/10.1007/s13753-021-00367-1.
Wobus, C., Porter, J., Lorie, M., Martinich, J., Bash, R., 2021. Climate change, riverine flood risk and adaptation for the conterminous United States. Environ. Res. Lett. 16 (9), 094034 https://doi.org/10.1088/1748-9326/ac1bd7.