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ORIGINAL ARTICLE

Estimating the loss-reduction effects of disaster preparedness and mitigation: An empirical study of US coastal states

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Abstract

As extreme weather events like floods and storms continue to increase, it is crucial to examine the degree to which various disaster preparedness and mitigation investments can lower these risks. In this research, we empirically examine the effects of multiple federal disaster aid programs on reducing subsequent flood- and storm-related damages across US coastal states. Our analysis distinguishes aid programs and their funded projects targeting different emergency management functions, including preparedness, nonstructural and structural mitigation, emergency response and protective measures, and rehabilitation of public infrastructure. We construct panel data of more than 1800 US counties over the years 2000–2019 and estimate a fixed-effects model with time-varying county-level socioeconomic and demographic characteristics. We find that disaster aid generally helps mitigate property damages, although this loss-reduction effect varies by program. Among all aid programs, the Emergency Management Performance Grant results in the largest reduction of future flood damages. The Public Assistance grants supporting emergency work are also found to exert a strong effect on risk reduction. We also find that the impacts of disaster aid are higher in coastal counties. Our study is one of the first few examining the resilience implication of disaster aid in coastal counties, and our results underscore the importance of investing in capacity building, contingency planning, and consistency in maintenance.

KEYWORDS
coastal communities, disaster aids, disaster preparedness, flood, mitigation, storms

1 | INTRODUCTION

As climate change unfolds, coastal communities are exposed to increased risks of natural hazards including hurricanes, flooding, storm surges, inundation, and rising sea levels. Some of these environmental hazards periodically turn into catastrophic disasters and pose severe threats to the livelihood of coastal residents (Intergovernmental Panel on Climate Change (IPCC), 2012). Around 40% of the US population lives in coastal counties, which contribute more than \$9 trillion in goods and services to the national economy, according to the National Oceanic and Atmospheric Administration (NOAA, 2022). Rapid population growth and economic development in the coastal areas have further heightened local climate risks, making it imperative to develop strategies for mitigating, preparing for, and adapting to natural hazards in the long term.

Although the conventional wisdom holds that taking preparedness and mitigation measures helps lower disaster risks, less is known about the degree to which such actions can mitigate future losses. Notably, both preparedness and mitigation are essential components of emergency management and involve activities that typically occur before a disaster strikes.[1] According to Donahue and Joyce (2001), mitigation includes activities intended to modify the causes of hazards, reduce vulnerability and potential losses from hazards; preparedness relates to activities that enhance the readiness of households and communities to respond to disasters effectively. Despite their importance in policy practice, there remain critical gaps in the scientific literature about the benefits of disaster preparedness and mitigation and, in particular, their varying levels of cost-effectiveness in risk reduction given the wide array of options ranging from stockpiling emergency supplies to building seawalls along the coast (Miao, 2018a). Existing research on disaster-related projects

[1] Modern emergency and disaster management typically include four phases including mitigation, preparedness, response, and recovery.

has predominantly focused on mitigation, with much less attention given to the benefits of preparedness investments (Mechler, 2016; Shreve & Kelman, 2014). Much of the existing research utilizes engineering-based probabilistic loss models to estimate the avoided damages due to certain protective measures and facilities (Davlasheridze et al., 2019; Kousky et al., 2019). Few studies examine the loss-mitigating effect of disaster-related spending using causal inference and observational data (Davlasheridze et al., 2017, Davlasheridze & Miao, 2021a; Healy & Malhotra, 2009). Yet these studies focus mostly on the average effect of aggregate mitigation spending without distinguishing among various types of projects (Healy & Malhotra, 2009; Welsch et al., 2022).

This research responds to the growing call for a more rigorous, empirically driven approach to assessing the economic benefits of disaster preparedness and mitigation investments. In the study, we examine the effect of major federal government disaster programs' spending on the flood- and storm-related losses across the US coastal communities. The key objective is to estimate whether and the extent to which different types of disaster program spending affect property damages from subsequent disasters and thus shed light on the economic returns on these investments. Our empirical analysis includes five federal disaster grant programs including Emergency Management Performance Grant (EMPG), Public Assistance (PA), Hazard Mitigation Grant Program, Flood Mitigation Assistance (FMA), and Pre-Disaster Mitigation (PDM) Grant programs. We use the grant funds data to measure government investments related to different dimensions of disaster mitigation and preparedness. To perform the analysis, we construct a panel dataset of US counties over the period 2000–2019 and model disaster losses as a function of cumulative government spending by program and project types, the physical intensity of flooding and storms, and a county's socioeconomic and demographic characteristics.

This research contributes to disaster economics and hazard literature in several ways. First, using the administrative data on federal disaster aid for localities, we are able to identify and distinguish government funds allocated for preparedness and mitigation and examine their cost-effectiveness. By taking this approach, we address an important gap in the literature related to the limited knowledge of the effectiveness of disaster preparedness. Second, this study is also one of the first few that examine preparedness and mitigation efficacy in coastal regions. Our focus on the major coastal hazards including floods, hurricanes, and severe storms carries important economic and policy relevance. Hurricanes and flooding are the costliest natural hazards in the United States (Miao et al., 2018). As climate change intensifies and sea level rises, coastal communities are facing disproportionately higher risks from the climate- and weather-related hazards. Considering the geographical specificity of these hazards, our research further elucidates the heterogeneous effects of government disaster funds across regions (including Atlantic, Gulf of Mexico, Pacific, and Great Lakes). Third, our research adds to the growing body of research on government disaster aid (e.g., Davlasheridze & Geylani, 2017; Deryugina et al., 2018; Davlasheridze & Miao, 2021a, 2021b) by exploring the efficacy of grant funds for enhancing community resilience. Findings from this study would provide policy implications for federal grant programs and local emergency management. In particular, the major federal disaster mitigation programs typically require state and local applicants to incorporate cost–benefit estimates of proposed projects, whereas such estimates are hard to make for many preparedness and other nonstructural projects. Our estimates should be particularly useful for guiding decisions related to disaster spending and aid allocation, project-based assessment, and benefit–cost analysis.

The rest of this article is organized as follows. The next section provides an overview of the literature, followed by sections describing the disaster programs we study, our data, and empirical strategy. We present our results in Section 6 and conclude with a discussion of the main findings, policy implications, and limitations of this research.

2 | RELEVANT LITERATURE

In this study, we focus on government investments in disaster preparedness and mitigation that help build community resilience to environmental hazards. As noted above, the existing disaster literature often conflates preparedness with mitigation because they both involve activities undertaken before disaster strikes to protect public safety and reduce risks. Nonetheless, mitigation and preparedness are different in their functions and scope of activities. Mitigation focuses on long-term measures that reduce the consequences and social impacts of hazards. For example, typical mitigation projects include protective structures (e.g., seawalls, dams, and levees for protecting against flooding and storm surges) and nonstructural measures (e.g., building codes and regulations, and managed retreat from risky locations).

By contrast, preparedness focuses more on short-term measures that improve readiness to respond to emergency situations and foster quick recovery (Levac et al., 2012; Donahue et al., 2013; National Resource Council, 2006; Sutton & Tierney, 2006). As a broad concept, disaster preparedness consists of a wide range of activities, including, but not limited to, developing disaster or emergency plans, stockpiling resources and supplies, acquiring hazard risk information and knowledge, and conducting exercises and drills. In the context of emergency management, the Federal Emergency Management Agency (FEMA) defines preparedness as "establishing authorities and responsibilities for emergency actions and gathering the resources to support them" (Federal Emergency Management Agency (FEMA), 2010; 4-1). Typical preparedness guidelines require government or public agencies in a jurisdiction to assign or recruit staff for emergency management duties, train personnel, develop plans, procedures, and networks, designate or procure equipment and materials for emergency responses, as well as conduct disaster education (Moynihan, 2009; Norwegian Refugee Council (NRC), 2006). Yet, some activities may fall under the umbrella of both preparedness and mitigation, such as developing evacuation plans and warning systems and communicating disaster risks (Sutton & Tierney, 2006).

With regard to assessing preparedness and mitigation investments in terms of their loss-reduction benefit, existing research has taken different approaches to address this question, which we review in more detail below. But these research efforts have focused more on structural mitigation measures or "hard resilience" rather than disaster preparedness and other nonstructural measures or "soft resilience" (Davlasheridze et al., 2019; Mechler, 2016; Shreve & Kelman, 2014). Specifically, several studies examined exercises and drills and provided evidence on their efficacy for improving preparedness knowledge and performances (Agboola et al., 2013; Skryabina et al., 2017). But these studies did not relate their findings to loss mitigation and provided little information about the economic cost and benefits of conducting these activities.

The lack of preparedness analyses is due to several challenges, as discussed in Kousky et al. (2019). First, preparedness activities are less discrete than the bricks-and-mortar mitigation projects. The latter often involves a one-time investment with predictable operating and maintenance costs, which are easier to quantify. By contrast, the scope of preparedness activities is harder to define and often evolving. Second, most infrastructure-related mitigation projects have capacity specifications (e.g., a levee that can protect against a 500-year flood) with predictable protection benefits, whereas preparedness is highly based on human activities and social interactions. There is considerable uncertainty and variability in these social outcomes and their actual influence on loss mitigation.

Existing empirical disaster research uses different approaches to evaluate investment in disaster risk reduction. Many studies have conducted benefit–cost analysis (BCA), which is a well-established method for identifying and monetizing the benefits and costs, discounting future values, and calculating the benefit-cost ratio (BCR) of a project. These studies often utilize engineering-based probabilistic loss estimation models to project the expected damage with and without specific mitigation measures; the avoided damages are considered to be the benefit (Davlasheridze et al., 2019; Kousky et al., 2019). For example, a study conducted by the National Institute of Building Sciences (NIBS) (NIBS, 2005) estimated an average 4:1 BCR using historical data on FEMA's hazard mitigation projects (i.e., $1 mitigation spending would reduce future disaster losses by $4). Their 2017 study and more recent 2019 report suggested an average BCR of 6:1 for selected federal mitigation grants (NIBS, 2017, 2019).[2]

Although most disaster-related BCA studies have suggested positive economic gains from risk reduction measures, their BCR estimates vary significantly by hazard type, location, and type of mitigation measures and are sensitive to specific assumptions, methodologies, and parameter choices (Hawley et al., 2012; Mechler, 2016; Shreve & Kelman, 2014). For example, the BCR estimated by NIBS (2005) varies from 1.5 for earthquake mitigation and 5.1 for flood mitigation. The study also estimated a much lower BCR of 1.4:1 for most process grants that involve hazard planning, due to the lack of empirical evidence on process-related community planning activities (Kousky et al., 2019). Another example is that the Congressional Budget Office (CBO) employed different discounting and extrapolation methods and found a lower BCR of 3:1 for federally funded mitigation projects (Congressional Budget Office (CBO), 2007).

Another approach for estimating the benefits of non-market goods and certain public services (e.g., preparedness and mitigation measures) is to elicit the average individual willingness to pay (WTP) for such goods using a contingent valuation (CV) approach. For example, a recent study by Wehde et al. (2021) estimates that the mean WTP for a weather app that provides continuously updated probabilistic hazard information is 7.53 per person, which is converted into an estimated value of $901 million—$1.56 billion based on the US population. Nonetheless, it should be mentioned that the CV approach is often expensive to implement because it relies on surveys. The respondents' stated preferences can suffer from hypothetical bias, where they tend to report WTP higher than their actual WTP because the situation is unrealistic (Champ & Bishop, 2001).

In addition to the engineering loss models and CV approach, a handful of studies have used econometric modeling techniques to examine the effect of public mitigation spending on actual disaster losses so as to infer the economic value of such investment (e.g., Davlasheridze & Miao, 2021a; Davlasheridze et al., 2017; Healy & Malhotra, 2009; Petkov, 2023). These studies commonly use data on government disaster aid or certain public expenditure as a measure of protective investment. For example, Healy and Malhotra (2009) compared the effects of federal disaster protection spending and relief aid spending on county-level disaster damages. They estimated that a $1 increase in protection spending saves $15 in future disaster costs. Davlasheridze et al. (2017) modeled hurricane-induced property losses in the North Atlantic counties and found that a 1% increase in mitigation spending reduces damage in the following year by 0.21%, whereas the same increase in post-disaster response and recovery spending reduces damages by 0.12%.

In another study, Davlasheridze and Miao (2021a) examined the effect of multiple federal post-disaster aid programs on flooding- and storm-related damages. Their estimates suggest that 1% increase in public infrastructure and mitigation expenditure reduces losses by approximately 0.11%, which translates into an estimated $1.8 in avoided damage for $1 spending. Welsch et al. (2022) used a dynamic panel feedback model to estimate the loss-reduction effect of three major federal mitigation programs. They estimated that a 100% increase in mitigation spending reduces flood damages

[2] These studies employed the loss model, HAZUS-MH, developed by FEMA and estimated the benefits on a variety of impact matrices including direct property damages, induced damages, societal losses (e.g., deaths and displaced households), and other direct and indirect economic losses.

by approximately 9% in the next year, which translates into a wide range of $208,350–$405,188 in the total social benefits. Petkov (2023) examined the loss-mitigating effect of federal disaster expenditures and local public expenditures and estimated that $1 public spending can mitigate up to $3 in losses over 20 years.

Our study is similar to the abovementioned empirical research but focuses on the loss-reduction effect of government investments in preparedness and mitigation separately. This ex post analysis based on empirical data and causal inference is a useful approach that allows us to examine the causal relationship between the treatment (e.g., preparedness and mitigation spending) and disaster damages. Moreover, using disaster program expenditure data provides a unique advantage for evaluation purposes because the project costs are known and we can identify different types of disaster-related projects (preparedness vs. mitigation).[3] Nonetheless, we note that using the federal disaster aid data does not include all government spending on disaster preparedness and mitigation, especially at the local level. It has been an empirical challenge to collect data and measure precisely local government spending on disaster preparedness. Furthermore, depending on the program design, federal disaster grants may either increase local government spending (e.g., as a result of the cost-share requirement of federal aid) or crowd out local disaster spending (particularly when urgent needs are met by federal funds). It has also been pointed out in the literature (Davlasheridze & Miao, 2019) that federal disaster relief can create the moral hazard problem by establishing the expectation for future disaster aid and lowering the local incentive to invest in disaster preparedness and mitigation. These complex behavioral responses triggered by federal aid may potentially counteract its effect on risk mitigation.

3 | POLICY BACKGROUND

In this study, we examine three major types of federal disaster grant programs, which are briefly discussed below.

3.1 | Emergency Management Performance Grant (EMPG)

The EMPG is a major disaster preparedness grant program administered by the FEMA. Authorized by Section 662 of the Post Katrina Emergency Management Reform Act and the Robert T. Stafford Disaster Relief and Emergency Assistance Act, the program provides federal resources to state, local, tribal, and territorial governments (primarily emergency management agencies) in preparing for all hazards. The key goal of the EMPG Program is to support a comprehensive, all-hazard emergency management approach.[4] The program has funded projects including hazard identification and risk assessment, updating emergency plans, designing and conducting exercises, enhancing training capabilities and emergency management organizations and structures (e.g., establishing emergency operating centers). Given the scope of its projects, we consider the EMPG-funded projects an appropriate and highly relevant measure of disaster preparedness spending.

3.2 | Hazard mitigation assistance

FEMA administers three major hazard mitigation assistance programs, including the Hazard Mitigation Grant Program (HMGP), PDM Grant, and FMA. All three programs focus on reducing or eliminating long-term risks from future disasters. The HMGP, which is the largest in size, provides grants to state, local, and tribal governments only after a major disaster declaration is issued by the President, whereas the other two grant programs do not require a presidential disaster declaration (PDD).

All these grant programs fund a variety of projects including property acquisitions, stormwater management, structural elevation, floodproofing and retrofit, flood control structures, warning systems, hazard mitigation planning and risk assessment, and public education activities. Given our research interest in disaster preparedness, we categorize these funded projects into the preparedness or "soft resilience" (including planning, risk assessment, public education, and warning system) and mitigation or "hard resilience" (e.g., property acquisition and demolition, structural elevation and retrofit, flood control infrastructure).

3.3 | Public Assistance

As FEMA's largest disaster aid program, the PA program provides grants to state, local, and tribal governments following a PDD. The program funds immediate disaster response (including debris removal and emergency protective measures such as providing equipment and supplies necessary for responding to emergencies) and permanent work (including restoration and repairs of damaged public infrastructure, water control facilities, public buildings, parks, and recreational facilities). We include PA grants here because these projects have a public good nature by assisting communities to quickly respond to and recover from a disaster event. Although the projects related to emergency response are primarily used for the PDD incident that already occurred, some

[3] In addition to the risk reduction efficacy of disaster aid, several studies have examined the aid effect on other socioeconomic and behavioral outcomes including public housing provision (Davlasheridze & Miao, 2021b), business survival (Davlasheridze & Geylani, 2017), and flood insurance purchases (Kousky et al., 2019; Davlasheridze & Miao, 2019). For a more comprehensive review of the literature on disaster aid and its loss-reduction efficacy, see Davlasheridze and Miao (2021a) and Miao (2018b).

[4] Note that FEMA administers multiple preparedness grant programs and almost all others (e.g., Homeland Security Grant Program) target terrorism and do not have an all-hazard focus as the EMPG does. Therefore, we do not include other preparedness grant programs in this study.

of the remaining resources and supplies (e.g., facilities and equipment) can be used to support future disaster preparedness activities. The funded public works projects typically involve the restoration of public facilities and infrastructure to enhance their hazard mitigation utility. Considering these distinctive attributes of PA-funded projects, we assign the PA grants into two categories: (i) funds for emergency work and (ii) funds for permanent work.

4 | SAMPLE AND DATA

Given our specific research interest in coastal communities and coastal hazards, we use a sample, including all the US coastal states (AL, AK, CA, CT, DE, FL, GA, HI, IL, IN, LA, MA, ME, MD, NH, MI, MN, MS, NC, NJ, NY, OH, OR, RI, SC, TX, VA, WA, WI) across four major coastal regions (Atlantic, Great Lake, Pacific, and the Gulf coast). Our unit of observation is a county-year, and we compile a balanced panel dataset combining data on disaster outlays, property damages, hazard magnitude, and county-specific socioeconomic and demographic characteristics over the 2000–2019 period.

We collect data on disaster grants and expenditures primarily from FEMA. Several things are important to note here. First, FEMA's data on EMPG only include projects that have been funded since 2010. Therefore, we supplement this dataset with the program-specific expenditure information (before 2010) from Census Bureau's Consolidated Federal Funds Report. Yet, the vast majority of EMPG projects were funded after 2010. Second, some of FEMA's assistance programs described above provide aid on a cost-share basis; specifically, for PA and all hazard mitigation assistance programs, the federal government pays for up to 75% of the eligible project expenses, and the remainder is paid by the state and local governments. For these programs, we use the entire project costs (including the federal awards and state and local match spending) to measure the full amount of preparedness or mitigation spending in a locality (still referred to as disaster aid for simplicity). Third, federal grants from all these FEMA programs were provided to both state governments and county governments as well as to municipalities and tribal governments. For smaller governments such as municipalities and tribes, we assign their received aid to the county where they are located. We note that some grants from these federal programs are directly allocated to state governments (e.g., a large proportion of the EMPG grants are awarded to state emergency management agencies). For such cases, we assume that these grants enhance a state's overall emergency management capacity and benefit all people within that state equally. Specifically, we first calculate the grants-to-states per capita (state's received aid or project costs divided by the state's population) in a given year and then add that to the per capita disaster aid (including local match spending) received by each county in that state in the same year. The sum of the annual disaster outlay flows is used for constructing disaster aid stocks based on a perpetual inventory model (described in more detail in the next section).[5]

The disaster loss data are obtained from the Spatial Hazards Events and Losses Database for the United States (SHELDUS). SHELDUS reports county-level estimates for direct losses caused by multiple natural hazards, including hurricanes, floods, earthquakes, droughts, wildfires, tornadoes, severe storms/thunderstorms, and winter weather. Its loss estimates for the meteorological and hydrological disaster events are largely based on the Storm Events Database maintained by the NOAA's National Weather Service (NWS).[6] To construct our dependent variable, we calculate the annual damage from floods, hurricanes, severe storms, and coastal storms in a county-year. Figure 1 displays the average flood- and storm-induced damage per capita in our sample counties from 1960 to 2019.

It is important to note that SHELDUS' disaster damage reporting has certain limitations such as temporal bias, threshold bias, and accounting bias (Gall et al., 2009). Specifically, SHELDUS uses the lower bound of the range of the estimated losses and only includes events causing at least $50,000 in property damage or causing at least one fatality. This approach thus underreports losses for low-damage events. Yet our sample covers a more recent period (2000–2019) when NWS has started reporting losses from smaller scale disaster incidents, which helps mitigate the threshold biases. Recent research (e.g., Bakkensen & Blair, 2020; Gallagher, 2023) has also noted other systematic biases in disaster damage reporting, that is, disaster losses are more likely to be underreported in counties with smaller populations and more socially disadvantaged groups (lower income, racial minorities), which can potentially bias our estimates of disaster aid effects.

Disaster losses are heavily influenced by the physical magnitude of natural hazards, which are accounted for in our empirical analysis. To measure the flood hazard, we follow the approach in Davlasheridze and Miao (2019, 2021a, 2021b) to exploit the annual rainfall variation at the county level. Using the precipitation data from the National Climate Data Center's Global Historical Climatology Network, we construct a rainfall anomaly variable, which measures the proportional deviation of a county's precipitation in year t from its long-run average during the 1960–2000 period.[7] Thus, a positive value indicates excessive rainfall and possible flooding conditions in a county year. As for hurricanes and tropical storms, we use the geospatial storm data from NOAA's International Best Track Archive for Climate

[5] We also conduct a sensitivity test by using only the disaster grants directly allocated to counties, which is reported in the Appendix.

[6] For flooding, hurricanes/tropical storms, and severe storms, SHELDUS collects the damage estimates from NOAA's National Centers for Environmental Information (NCEI, formerly National Climatic Data Center) Storm Data and Unusual Weather Phenomena. These damage estimates reflect direct loss from natural disasters and are typically obtained from emergency managers, US Geological Survey, US Army Corps of Engineers, power utility companies, and newspaper articles.

[7] Specifically, we map the weather stations to counties based on their latitude and longitude and compute the annual total rainfall for a given county-year observation. For counties with multiple stations, we take the average of their annual sum.

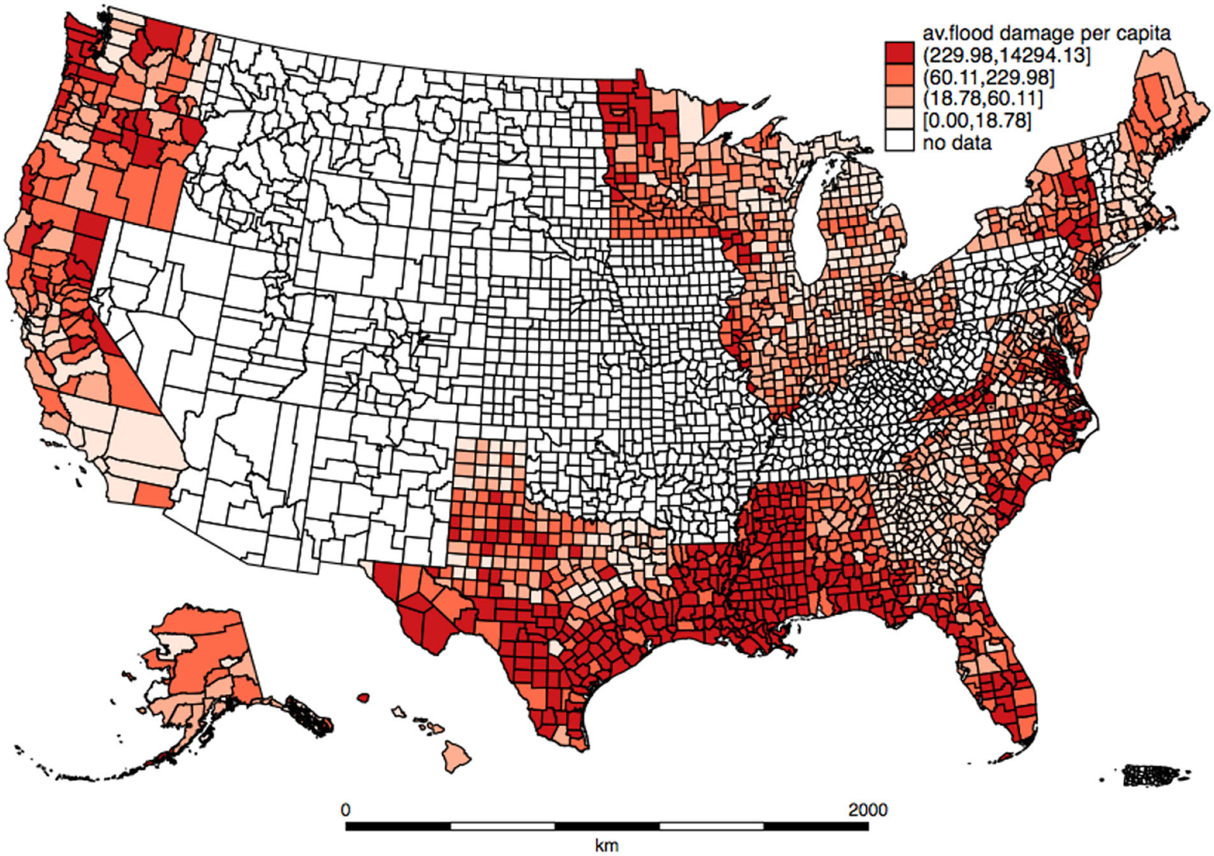

FIGURE 1 Average per capita property damage from floods and storms (in 2015 dollars) over 1960–2019.

Stewardship.[8] We map the storm data to coastal counties and calculate the maximum wind speed associated with these storms that occurred within a county in a given year. We use the wind speed data to identify storm magnitude and then calculate the count of hurricanes of different categories using Saffir–Simpson hurricane wind scales (Category 1, Category 2, and Category 3 and higher) in a county-year observation.

It has been widely recognized that natural disaster losses are place-based and vary considerably depending on a community's economic exposure, social vulnerability, and capacity to protect against natural hazards (Kahn, 2005; Cutter et al., 2003). To control for the socioeconomic conditions, we include a county's per capita income and population, using the data from the Bureau of Economic Analysis. We also control for a county's annual poverty rates and median housing values using data from the US Census Bureau. Regarding demographics, we include a variable measuring the percentage of the African American population using the data from the National Center for Health Statistics. We also include a variable measuring a county's recent disaster experience using the count of flood- and storm-related PDDs (with PDD data retrieved from FEMA). Table 1 reports the summary statistics of our main variables.

[8] The IBTrACS data, which are compiled from numerous tropical cyclone datasets, provide the most complete global set of individual storm events and track their positions.

5 | EMPIRICAL MODEL

To identify the effect of government preparedness spending on disaster losses, we estimate a panel fixed effects model specified in the following equation:

$$\begin{aligned}\ln(Loss_{ct}) &= \ln(EMPG_{ct-1})\,\beta_1 + \ln(HMG_{ct-1})\,\beta_2 \\ &\quad + \ln(PA_{ct-1})\,\beta_3 + Hazard_{ct}\beta_4 \\ &\quad + X_{ct-1}\alpha + \lambda_{\mathrm{t}} + \lambda_{\mathrm{c}} + \lambda_{region*t} + \varepsilon_{\mathrm{ct}} \qquad (1)\end{aligned}$$

The dependent variable, $Loss_{ct}$, measures the property damage caused by flood- and storm-related disasters in county c in year t. Disaster damage is a function of the physical magnitude of the contemporaneous shock, denoted as *Hazard,* including multiple variables measuring a county's annual rainfall anomaly and the number of storm events of different scales. Our key variables of interest include the multiple federal disaster grant programs, including the EMPG, Hazard Mitigation Grant Programs (denoted as HMG), and PA. For HMG, we combine all project data from the three FEMA programs discussed above but distinguish preparedness grants (or "soft resilience" including projects such as mitigation planning, training, and education programs) from mitigation grants (or "hard resilience" including property

TABLE 1 Summary statistics of main variables.

Full sample (N = 37,540|1877 counties)

Variables	Mean	Std. Dev.	Min	Max
Damage per capita (log)	0.960	1.620	0	13.455
Damage per capita (unlogged)	93.941	2914.124	0	348,518.500
EMPG grants (log)	0.630	1.025	0	6.993
EMPG grants (unlogged)	1.729	6.962	0	544.676
Mitigation grants—preparedness (log)	0.792	0.971	0	7.754
Mitigation grants—preparedness (unlogged)	2.551	19.238	0	1165.285
Mitigation grants—structural mitigation (log)	1.572	1.587	0	10.053
Mitigation grants—structural mitigation (unlogged)	15.305	113.726	0	11,612.410
Public Assistance—emergency response (log)	2.736	1.751	0	11.199
Public Assistance—emergency response (unlogged)	51.460	556.119	0	36,535.360
Public Assistance—permanent works (log)	3.158	1.849	0	11.077
Public Assistance—permanent works (unlogged)	84.677	754.142	0	32,335.970
Rainfall anomaly	0.259	1.210	−6.825	8.999
No. of hurricanes (Category 1)	0.001	0.032	0	2
No. of hurricanes (Category 2)	0.000	0.019	0	2
No. of hurricanes (Category 3+)	0.000	0.015	0	1
No. of flood & storm PDDs in last 5 years	1.787	1.655	0	11
Personal income per capita (log)	10.587	0.237	9.634	12.190
Population (log)	10.688	1.402	5.557	16.129
Median housing values (log)	11.858	0.488	9.940	14.223
Poverty rates (%)	15.319	6.338	2.500	49.300
Percentage of African American (%)	12.626	16.583	0.000	86.732

Sample of coastal counties (N = 12,500|625 counties)

Variables	Mean	Std. Dev.	Min	Max
Damage per capita (log)	0.987	1.799	0	13.455
Damage per capita (unlogged)	192.890	4864.225	0	348,518.500
EMPG grants (log)	0.681	1.077	0	5.445
EMPG grants (unlogged)	1.956	5.740	0	115.832
Mitigation grants—preparedness (log)	0.877	0.974	0	7.304
Mitigation grants—preparedness (unlogged)	2.520	13.949	0	743.121
Mitigation grants—structural mitigation (log)	1.803	1.679	0	10.053
Mitigation grants—structural mitigation (unlogged)	21.817	182.639	0	11,612.410
Public Assistance—emergency response (log)	2.878	2.036	0	11.199
Public Assistance—emergency response (unlogged)	100.983	956.525	0	36,535.360
Public Assistance—permanent works (log)	3.131	2.084	0	11.077
Public Assistance—permanent works (unlogged)	154.577	1286.820	0	32,335.970
Rainfall anomaly	0.257	1.173	−4.701	8.326
No. of hurricanes (Category 1)	0.002	0.048	0	2
No. of hurricanes (Category 2)	0.001	0.032	0	2
No. of hurricanes (Category 3+)	0.000	0.020	0	1
No. of flood and storm PDDs in last 5 years	2.109	1.870	0	11
Personal income per capita (log)	10.656	0.277	9.634	12.190
Population (log)	11.207	1.476	6.001	16.129
Median housing values (log)	12.083	0.539	10.325	14.223
Poverty rates (%)	14.535	6.184	2.5	45.7
Percentage of African American (%)	14.047	15.583	0	79.611

acquisition and relocation, retrofit, stormwater management, flood-proof) using two separate variables. For PA, we separate the emergency response expenditures from the public works project spending. Considering that disaster aid may have a long-term effect on reducing risks, we use a perpetual inventory model to accumulate county-level disaster aid (flow variables) from 1990 to year $t-1$. Specifically, the aid stock by program is calculated using the following equation:

$$\text{Aid Stock}_{ct} = \text{Aid Flow}_{ct} + (1-\rho)\ \text{Aid Stock}_{ct-1} \tag{2}$$

where ρ is the stock depreciation rate, which we assume to be 10%.[9] Using the perpetual inventory model with a depreciation rate allows us to account for the grants received earlier and put higher weight on the more recent disaster aid.[10] We normalized both the disaster damage and aid stock variables using the inverse hyperbolic sine function (Pence, 2006).[11] This approach approximates the logarithmic transformation as well as allows us to include observations with zero values for constructing a balanced panel of all county-year observations. Thus, we can interpret the estimated coefficients of disaster aid stocks in the form of elasticity.

It is important to note that the receipt of disaster aid may correlate with local community attributes such as socioeconomic factors, recent disaster experiences, and baseline geographic risks, all of which can simultaneously influence disaster damages. Thus, our model includes X_{ct-1}, denoting a vector of county-level socioeconomic and demographic variables, including per capita personal income, size of population, median housing values, percentage of black (%), and poverty rates (%). All these variables are lagged by 1 year to mitigate the endogeneity problem. We also include the cumulative count of flood and storm PDDs a county has experienced in the last 5 years (as part of X_{ct-1}) to account for its recent disaster experiences. λ_c denotes the county fixed effects, which control for a country's time-invariant unobserved characteristics such as its baseline geographic risks (proneness to flooding and storms), topography and long-existing risk-mitigating capacity (dams or levees that existed prior to our sample period), which can presumably influence its disaster damage as well. λ_t denotes the year fixed effects, which control for any national shocks common to all counties in the same year (e.g., changes in the federal disaster policy and grant provision, disaster damage reporting bias). In this model, we also include region-by-year fixed effects, $\lambda_{region*t}$, to account for unobserved time-varying factors that influence disaster damages in counties within the same region (Atlantic, Gulf of Mexico, Pacific, and Great Lakes). Finally, ε_{ct} denotes the error term. Standard errors are clustered at the county level to allow for heteroscedasticity and flexible correlation of errors over time between the clustering units. By using the two-way fixed effects model, our underlying assumption for identification is that after controlling for the aforementioned factors, our disaster aid stock does not correlate with the error term in the disaster damage function (i.e., other accounted factors that influence disaster damages). We discuss the potential limitations with this assumption at the end of this article.

6 | RESULTS

6.1 | Baseline estimates

Table 2 reports our results from the baseline model (Equation 1) using two different samples. Estimates in Column 1 are based on the full sample including all counties from coastal states (1877 counties in total), whereas Column 2 is based on a confined sample of coastal watershed counties only (625 in total), based on NOAA's classification.[12] We find that almost all the disaster aid stock variables are statistically significant with a negative sign, which suggests that more aid received by a county helps reduce its subsequent disaster damages when controlling for the exogenous hazard and other social factors. In Column 1, we show that the EMPG grants and PA grants targeting emergency response have relatively larger loss-reduction effects compared to the other disaster grants. Specifically, a 1% increase in the two aid (stock) variables is estimated to reduce flood- and storm-related damages in the following year by 0.08% and 0.07%, respectively. The other three aid variables, mitigation grants targeting preparedness activities or structural mitigation projects and PA grants targeting permanent works, are similar in the magnitude of their effects on reducing future damages.

Our results in Column 2 indicate that these disaster grants generally have greater effects on loss mitigation in coastal counties, except that the effect of PA grants for permanent works becomes statistically insignificant. The estimates of EMPG grants and PA grants targeting emergency response consistently show larger loss-mitigating effects relative to the other disaster grants. One percent increase in the two aid variables would reduce disaster damage by 0.19% and 0.15%, respectively. These findings suggest that communities at higher risk of flooding and storms are more effective in using federal disaster aid for mitigating local disaster risks. This is expected because disaster occurrence is more frequent in high-risk areas, and the benefits (in terms of loss avoidance) of investments in disaster preparedness and mitigation tend to also be higher in these regions.

[9] We also conducted a sensitivity test using a 5% depreciation rate in the perpetual inventory model to compute the disaster aid stocks. Our regression results using the alternative stock variables are highly similar to our baseline estimates. We report our sensitivity tests in the Online Appendix.

[10] For the first year's aid stock, we simply equate the aid in the first year (in 1990) to knowledge stock because most counties had zero aid. Our estimation sample starts in 2000, so we allow the disaster aid to accumulate for ten years before entering into the regression model.

[11] The formula for the inverse hyperbolic sine function is defined as (ln[y + (y^2 + 1)^0.5]).

[12] NOAA defines the coastal watershed counties as those where land use and water quality changes most directly impact coastal ecosystems. A county is classified as a Coastal Watershed County if one of the following criteria is met: (1) At a minimum, 15% of the county's total land area is located within a coastal watershed or (2) a portion of an entire county accounts for at least 15% of a coastal uses 8-digit cataloging unit.

TABLE 2 Modeling impact of disaster grants on damages.

	(1)	(2)
EMPG grants (preparedness grants-related)	−0.0785***	−0.189***
	(0.0221)	(0.0368)
Mitigation grants—preparedness	−0.0277*	−0.0591**
	(0.0148)	(0.0260)
Mitigation grants—structural mitigation	−0.0267**	−0.0481**
	(0.0112)	(0.0186)
Public Assistance—emergency response	−0.0656***	−0.147***
	(0.0150)	(0.0271)
Public Assistance—permanent works	−0.0275**	−0.0224
	(0.0127)	(0.0226)
Rainfall anomaly	0.297***	0.297***
	(0.00950)	(0.0192)
No. of hurricanes (Category 1)	2.438***	1.991***
	(0.533)	(0.558)
No. of hurricanes (Category 2)	2.608***	2.048**
	(0.951)	(1.035)
No. of hurricanes (Category 3+)	6.554***	7.422***
	(1.490)	(0.542)
No. of flood and storm PDDs in last 5 years	−0.000173	0.0217*
	(0.00662)	(0.0111)
Personal income per capita (log)	−0.0872	−0.510*
	(0.140)	(0.295)
Population (log)	−0.203	−0.698**
	(0.151)	(0.303)
Median housing values (log)	−0.0593	0.217
	(0.108)	(0.174)
Poverty rates (%)	−0.00534	−0.0166*
	(0.00481)	(0.00991)
Percentage of African American (%)	−0.0200**	−0.0314*
	(0.00852)	(0.0165)
Observations	37,540	12,500
Number of counties	1877	625

Notes: All the specifications include county FE, year FE and region by year FE. Column 1 includes all counties in US coastal states, and Column 2 and 3 includes coastal counties only. Standard errors are clustered by county.

Abbreviations: EMPG, Emergency Management Performance Grant; PDD, presidential disaster declaration.

$*p < 0.1$.

$**p < 0.05$.

$***p < 0.01$.

Across all specifications, we show that the contemporaneous hazard variables are all statistically significant with the expected positive sign, suggesting their strong predictive power for disaster damages. The estimated coefficients on the hurricane variables suggest disaster losses increase with the hazard magnitude, which is also consistent with our expectations.

Regarding the other county-level controls, we expect the socioeconomic variables to have a mixed effect on disaster damages because higher incomes or housing values (as well as lower poverty rates) capture greater, more expensive private assets exposed to natural hazards but also imply higher capacity to invest in risk mitigation. Although these variables are all insignificant in Column 1 (full sample model), we find personal incomes and poverty rates both negatively correlate with disaster damages (statistically significant at the 10% level), suggesting the multiple mechanisms through which socioeconomic status influences disaster outcomes. We also find that the population variable has a negative coefficient (statistically significant at 1% level) in Column 2. Although a larger population also implies greater human exposure to natural hazards, it is possible that localities with larger populations can have a higher capacity and more resources to undertake mitigation (such as protective infrastructure) as well as benefit from the economies of scale in undertaking protection against natural hazards (resulting in fewer per capita damages). Our results also indicate a negative correlation between the ratio of African American populations with disaster damages (in both Columns 1 and 2). The estimates indicate that a 1% point increase in the ratio of the Black population in a county is associated with a 2% and 3% decrease in disaster damage in the full sample and coastal counties, respectively. One possible explanation, as identified in the recent literature (e.g., Bakkensen & Blair, 2020; Gallagher, 2023), could be that disaster losses are not fully documented and thus underreported in communities with more disadvantaged groups such as racial minorities.

6.2 | Impact of cumulative disaster aid

As our disaster aid stock variable (constructed using the perpetual inventory model) places higher weight on more recently received disaster aid, this approach assumes that the economic value of disaster aid-funded projects depreciates over time. Yet we note that many projects, especially those involving public infrastructure, may take a longer time to be completed after federal aid is disbursed, and their mitigation efficacy may not necessarily decline over time. To further examine the temporal variations in the aid's effect, we use an alternative measure by calculating the sum of disaster grants (by program) received by a county in the last 10 years (year $t-10$ through year $t-1$) and regress the aid variables on the current year's damages (in year t). This approach allows for equal weight placed on disaster aid disbursed in different years and accounts for the potentially delayed effect of those structural mitigation projects.

Table 3 reports our results using the full sample and confined sample separately. We show that all aid variables are statistically significant and exert a negative effect on disaster damages in both columns. Similar to our baseline findings, the effects of disaster aid are generally larger in magnitude in the coastal watershed counties than the estimates based on the full sample, suggesting larger loss-mitigating effects in higher risk areas. Among all types of aid, the EMPG grant exhibits the largest effect for mitigating disaster damages in both columns, which is similar to our baseline estimates in magnitude. One noticeable difference from our baseline results is that the PA grants targeting permanent works become statistically significant for reducing disaster damages in coastal counties. This may suggest that this type of grant has delayed effects on loss mitigation.

In addition to estimating the average effect of disaster outlays in our baseline model, we further examine the heterogeneous loss-mitigating effects of disaster grants by regions (Atlantic, Gulf of Mexico, Pacific, and Great Lakes). In the results reported in Supporting Information Appendix, we find that loss-mitigating effects of disaster grants are more pronounced in the Gulf Coast region (in particular in its coastal counties).[13]

6.3 | Calculating the return on investments (ROI)

As we use a log-log model to estimate the aid effect, we interpret our estimated coefficients in the form of elasticity (i.e., percent change in expected damages with respect to a 1% increase in disaster aid stocks). This approach, however, makes it difficult to directly interpret the aid effect in dollar units and estimate the BCR of government investments in preparedness and mitigation. To infer returns on investment (i.e., return in terms of avoided disaster damage due to $1 spending on disaster preparedness and mitigation), we combine our estimated coefficients of aid stocks from regression analysis with the sample means of disaster damages and aid stocks. Specifically, we use the mean values of unlogged disaster aid stocks per county by year to gauge spending in dollars with a 1% increase in disaster aid. We use the sample mean of unlogged disaster damages as the baseline to quantify the amount of damages in dollars given a 1% increase in the damage variable. We calculate the return on investment (ROI) in dollar units as the disaster aid coefficient multiplied by the sample mean of disaster damage and then divided by the sample mean of the corresponding aid stock variable (beta*y/x, or the amount of disaster damage in dollars saved by 1% increase in disaster aid divided by 1% of disaster aid in dollars).

Table 4 (Panel A) reports our estimates based on our regression estimates in Tables 2 and 3, where our regression sample differs across columns. As a robustness check, we also use the sample mean of disaster aid stocks in county-year with positive aid only and the average flood damages for these observations as another baseline and reestimate the returns on investment by aid program, which are reported in Panel B. The estimates are generally similar to those in Panel A.

Overall, we find that the estimated ROIs are generally higher in coastal counties compared to the estimates for all counties in coastal states. This is because the estimated loss-reduction effect of disaster aid in coastal counties is larger in magnitude as well as the average disaster damages are higher in these counties. Among different aid programs, we show the EMPG grants, and mitigation grants targeting preparedness activities have relatively higher ROIs. We estimate that $1 spent on the EMPG program generates $3 in economic returns (i.e., avoided damage) on average and a return of $14 in coastal counties. The mitigation grants targeting preparedness and soft resilience activities reduce $5 in future damages in coastal counties. We note that the sample means of these two variables are much smaller than the other three aid variables, and a 1% increase in the former translates into

[13] In another extension (reported in the Appendix), we have examined the effect of disaster aid stocks on fatalities and injuries from flooding and storms using the same regression model and find that the aid effect is statistically insignificant.

TABLE 3 Modeling the loss-mitigating impact of disaster grants (10-year cumulative flows).

	(1)	(2)
EMPG grants (preparedness grants-related)	−0.0830***	−0.188***
	(0.0213)	(0.0364)
Mitigation grants—preparedness	−0.0225*	−0.0372*
	(0.0125)	(0.0217)
Mitigation grants—structural mitigation	−0.0216***	−0.0351**
	(0.00787)	(0.0151)
Public Assistance—emergency response	−0.0537***	−0.0898***
	(0.0124)	(0.0224)
Public Assistance—permanent works	−0.0220*	−0.0454**
	(0.0117)	(0.0212)
Rainfall anomaly	0.297***	0.296***
	(0.00950)	(0.0193)
No. of hurricanes (Category 1)	2.426***	1.988***
	(0.531)	(0.554)
No. of hurricanes (Category 2)	2.625***	2.081**
	(0.949)	(1.035)
No. of hurricanes (Category 3+)	6.550***	7.459***
	(1.514)	(0.543)
No. of flood and storm PDDs in last 5 years	−0.00404	0.0138
	(0.00639)	(0.0105)
Personal income per capita (log)	−0.111	−0.569*
	(0.140)	(0.298)
Population (log)	−0.199	−0.662**
	(0.152)	(0.310)
Median housing values (log)	−0.0475	0.244
	(0.108)	(0.172)
Poverty rates (%)	−0.00557	−0.0164*
	(0.00480)	(0.00990)
Percentage of African American (%)	−0.0204**	−0.0330*
	(0.00864)	(0.0172)
Observations	37,540	12,500
Number of counties	1877	625

Notes: All the specifications include county FE, year FE and region by year FE. Column 1 includes all counties in US coastal states, and Column 2 includes coastal counties only.
Abbreviations: EMPG, Emergency Management Performance Grant; PDD, presidential disaster declaration.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

a relatively small amount of spending in dollars. Nonetheless, the larger ROIs of the EMPG program are also driven by our regression estimates of its loss-reduction effect (shown in Tables 2 and 3). As noted earlier, EMPG funding generally results in the largest loss-reduction effect compared to other disaster aid programs. One possible explanation could be related to the "transiency" of the different disaster programs examined here. Disaster assistance programs contingent on PDDs can be considered to be "transitory" programs in the sense that they are only provided following large-scale disaster shocks. These programs are different from programs with a stable nature (e.g., EMPG) that are available on a regular annual basis and allow communities to identify gaps, strategies, and prioritize projects and ensure the continuity of existing funded projects. Because of the reactive nature of PDD-related aid programs, their funds are generally spent in a chaotic, post-disaster environment and may not yield the best desirable outcomes in terms of selecting the suits of the programs. Mismanagement of government-funded projects (Gelinas, 2016) and inefficient use of disaster funding have been the common criticism of disaster aid programs (Kousky & Shabman, 2017).

TABLE 4 Estimated returns on $1 disaster spending.

Panel A				
Corresponding coefficients	**Table 2 Column 1**	**Table 2 Column 2**	**Table 3 Column 1**	**Table 3 Column 2**
EMPG grants (preparedness grants-related)	4.265	18.636	2.546	12.048
Mitigation grants—preparedness	1.020	4.524	0.725	2.686
Mitigation grants—structural mitigation	0.169	0.425	0.121	0.299
Public Assistance—emergency response	0.120	0.281	0.075	0.128
Public Assistance—permanent works	0.031	(0.028)	0.019	0.042
Panel B				
Corresponding coefficients	**Table 2 Column 1**	**Table 2 Column 2**	**Table 3 Column 1**	**Table 3 Column 2**
EMPG grants (preparedness grants-related)	2.590	10.882	3.201	12.419
Mitigation grants—preparedness	1.019	4.523	0.740	2.723
Mitigation grants—structural mitigation	0.169	0.425	0.121	0.299
Public Assistance—emergency response	0.120	0.281	0.078	0.135
Public Assistance—permanent works	0.030	(0.028)	0.019	0.044

Notes: The ROI (i.e., disaster damage (in dollars) saved by $1 spending on disaster preparedness and mitigation) in Panel A is calculated as the disaster aid coefficient multiplied by the sample mean of disaster damage and then divided by the sample mean of the corresponding aid stock variable (beta**y*/*x*). The ROI reported in Panel B is calculated using the sample mean of disaster aid stocks in county-year with positive aid only and the average flood damages for these observations as another baseline and reestimate the returns on investment by aid program. Numbers in parentheses are derived from the estimated coefficients that are statistically insignificant.

Abbreviation: EMPG, Emergency Management Performance Grant.

Second, aid programs such as EMPG allow communities to build organizational capacity in advance by developing contingency plans, improving warning systems, and building operational facilities. EMPG funds can also be used to cover the maintenance and sustainment costs of existing projects to ensure continued functionality of vital public services (FEMA, 2021). Third, it is worth noting that compared to many other disaster aid programs, EMPG provides more aid directly to state emergency management agencies to support their preparedness functions, capacity-building activities and infrastructure. Considering organization capacity, it is possible that state agencies are more capable of utilizing federal aid to coordinate emergency management functions and allocate these resources more efficiently within a state. In another extension (reported in the Supporting InformationAppendix), we reestimated our baseline model using disaster aid only directly allocated to counties and found smaller estimates for the preparedness grants than those accounting for apportioned grants-to-states. Overall, our results suggest that disaster grants operated through state agencies can be more cost-effective for risk mitigation, which, to some extent, resonate with the findings in prior research (Miao et al., 2021) that decentralizing disaster mitigation funding can lead to inefficient protection.

Lastly, it is important to note that counties generally do not experience flooding or storms every year, as disasters are triggered by relatively rare natural events. Moreover, the tendency to experience damage varies spatially by place depending on geographic characteristics and other social vulnerability and resilience-related factors. There is also considerable variation across the country in the distribution of federal disaster assistance. In this context, our regression coefficients in the percentage term can be more useful when they are integrated with local average disaster damages and disaster expenditures to generate more meaningful ROI estimates.

7 | CONCLUSION

In this research, we empirically examine the effect of multiple federal disaster aid programs on reducing subsequent flood-related damages across US coastal states, with a particular focus on government expenditures on preparedness and mitigation. Our study distinguishes different types of grants targeting various functions, including emergency preparedness, mitigation (soft resilience/preparedness vs. hard resilience/structural mitigation), response (emergency protective measures), and recovery (permanent work). It is also the first to examine the resilience implications of disaster aid for coastal communities.

Our results show that disaster aid generally helps alleviate subsequent flood-related property damage at the county level, whereas this loss-reduction effect varies by program and by region. Among all disaster aid programs, we find that the EMPG results in the largest reduction of future damages: A 1% increase in the cumulative aid stock is associated with a 0.08% decrease in damages across US coastal states and reduces the damages in coastal counties by 0.19%. The PA grants supporting emergency response are also found to yield a strong loss-reduction effect: A 1% increase in the aid is expected to reduce subsequent flood damage by 0.07%–0.15%. In terms of regional heterogeneity, we show that the impacts of disaster aid are stronger in coastal counties compared to non-coastal counties. To put these estimated coefficients into perspective, we use the sample means of disaster aid and damages variables to estimate the return on government investment in disaster management. We estimate that $1 spent on the EMPG program generates $3 economic returns (in the form of avoided damage) on average and a return of $14 in coastal counties. The mitigation grants targeting preparedness and soft resilience activities reduce $5 in future damages in coastal counties.

We also acknowledge the limitations of this research. First, although, in this article, we focus on the loss-reduction effect of disaster outlays, we should note that such grants and grant-funded projects may cause unintended consequences, for example, by crowding out other public or private mitigation investment or promoting continued development in hazard-prone areas (Davlasheridze & Miao, 2021; Burby, 2006) and thus counteract its efficacy in risk mitigation. These grants may also possibly disrupt other non-disaster-related capital projects, and their benefits may not necessarily accrue to the recipient localities (Kousky, 2014). It is important to note that our study does not account for all these follow-on behavioral responses, and our estimates would reflect the average net effect of disaster aid programs. An important caveat of our estimation strategy is that the FE regression, even with the lagged explanatory variables and county- and year-specific fixed effects, may not fully eliminate endogeneity bias between damages and disaster aid variables if there are unobservable factors that correlate with both the aid variable and the error term. Whether the bias in estimated coefficients is upward or downward requires knowledge about how these omitted unobservables affect both the endogenous variable and the dependent variable in the model (Wooldridge, 2016). The direction of the bias can be determined if we are able to establish how the omitted factors correlate with the endogenous variable and the dependent variable in the model. Generally, biases are downward (i.e., the true effect is larger than that shown by estimated coefficients) if the correlation between the omitted variables and endogenous variable (i.e., disaster aid), and the correlation between the omitted variables and dependent variable (i.e., damage), run in opposite directions. For example, unobserved variables such as the local capacity to apply for funding (or leverage political power to make their voices heard) that increase the receipt of disaster aid and will likely negatively correlate with observed damages (if we assume that localities with greater capacity are generally more resilient and able to mitigate risk more effectively). Thus, omitting such factors may cause a downward bias in our model. Moreover, it is possible that the public disaster grants we examined in this article may positively correlate with the outlays of other federal disaster programs, and the latter may simultaneously influence disaster damages (if other unobserved disaster aid also reduces disaster damages, then our FE estimates will again be downward biased). We have noted that previous research (Davlasheridze et al., 2017) has employed instrumental variables (such as political leaning, percent of swing voters) to address the endogeneity of disaster aid, but this approach cannot be applied here as we have multiple disaster aid variables which are distinguished based on project and program type.

Our research can be further extended in several directions. First, one direction for future research is to combine surveys and administrative/observational data to assess the efficacy of public investment against natural hazards. For instance, a survey instrument for local emergency managers will allow for collecting more detailed information about not only program/project spending but also specific activities (e.g., drill and training) at the locality level. Such data could be combined with disaster damages to infer the loss-reduction effect of specific preparedness and mitigation projects. It is also important for future research to compare these ex post empirical estimates with estimates based on CV and WTP surveys on similar preparedness activities.

Second, prior research suggests that the distribution of federal disaster aid is often influenced by various factors such as politics and local community attributes (Garrett & Sobel, 2003; Davis et al., 2018; Domingue & Emrich, 2019). Moreover, counties with more frequent exposure to flood and storm hazards tend to receive more disaster aid and spend more on preparedness and mitigation. More research will be needed to examine the distribution of FEMA-funded preparedness and mitigation projects and how these investments (as an outcome variable) may correlate with a county's socioeconomic characteristics and hazard exposure. Such analysis will also help shed light on the equity issue in disaster grant allocation. Third, this research focuses predominantly on government-funded public preparedness and mitigation projects and does not consider the activities carried out by individuals and households. Future research should seek to provide more empirical evidence on the loss-reduction effects of private preparedness and mitigation behaviors.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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