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# Estimating the Loss Reduction Effects of Disaster Preparedness: An Empirical Study of U.S. Coastal States

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## 1. Introduction

How societies cope with disasters is a question that has long concerned researchers and policymakers. This issue is particularly urgent for coastal communities as they are exposed to a variety of natural hazards such as hurricanes, flooding, storm surge, tsunamis, and rising sea levels. These hazards periodically turn into catastrophic disasters and pose severe threats to the livelihood of coastal residents that account for 40 percent of the U.S. population. To effectively address the growing coastal risks, particularly in light of climate change, requires preemptive actions in preparing for disasters before they strike.

Preparedness is an essential part of emergency management and is expected to deliver significant societal benefits by improving public safety, reducing disaster losses, and enhancing community resilience. Despite its importance in policy practice, there remains a critical gap in the scientific literature about the economic value of disaster preparedness. Assessments of disaster-related public projects have predominantly focused on mitigation, with much less effort to identify and quantify the outcome, impact, and benefits of preparedness due to the difficulty of measuring the wide array of preparedness activities and inputs (Mechler, 2016; Shreve and Kelman, 2014).

This research responds to the growing call for a more rigorous, empirically-driven approach to assess the economic benefits of disaster preparedness. In this study, we examine the effect of government spending on preparedness and mitigation projects on the flood- and storm-related losses across the U.S. coastal communities. The key goal is to analyze the causal link between preparedness and disaster losses, estimate the loss-mitigating effect of preparedness investments, and gauge the economic returns on such investments. Our empirical analysis includes multiple federal disaster grant programs (including Emergency Management Performance Grant, Hazard Mitigation Assistance and Public Assistance). The grant data are used to measure government investments in different dimensions of preparedness separately from mitigation projects. We construct a panel data set of U.S. counties over the period 2000 – 2019 and model disaster losses as a function of cumulative spending on preparedness or mitigation by programs, the physical intensity of flooding and storms, and a county's socioeconomic and demographic characteristics.

This research is one of the first to estimate the loss-reduction benefit of government investments in community-level disaster preparedness. Based on empirical, observational data, our approach is different from most disaster-related benefit-cost analyses using probabilistic loss estimation models. Drawing upon disaster aid data, we are able to distinguish preparedness from mitigation projects, develop more precise estimates of the effect of preparedness spending, and also compare the cost-effectiveness of different types of disaster projects and programs (preparedness vs. mitigation). With a particular focus on coastal areas, this project sheds light on the benefits of preparedness for coastal hazards (e.g., floods, hurricanes, and storm surge) and the heterogeneous effects of preparedness investments across regions. Findings from this project would provide policy implications for federal grant programs and local emergency management. Our estimates should be particularly useful for guiding decisions related to disaster aid allocation, project-based assessment and related benefit-cost analysis.

## 2. Conceptual issues and relevant literature

Preparedness generally refers to the activities and measures undertaken in advance of an imminent threat that improve readiness to respond to a disaster and foster quick recovery (Levac et al. 2012; Sutton and Tierney, 2006; Donahue et al. 2013). 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. Yet the scope of preparedness activities varies substantially by the acting agent (e.g., individuals, households, business organizations, community groups, and government).

In this study**,** we focus on government-led actions and investments in community preparedness. 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" (FEMA, 2010; 4-1). Typical preparedness guidelines require government or public agencies in a jurisdiction to assign or recruit staff for emergency management duties, develop plans and procedures how to respond when an emergency or disaster occurs, train personnel to respond, designate or procure facilities, equipment, and other materials for carrying out assigned duties. Additionally, governments play a critical role in promoting individual and business preparedness by raising their risk awareness through education, information and risk communication. Government-led preparedness actions also heavily involve coordination and collaboration across different organizations and networks (Kapcucu, 2006; Moynihan, 2009; Kapcucu et al. 2010).

Three things are worth noting about the scope of preparedness activities. First, while most of the existing disaster research examines preparedness measures for a particular natural hazard such as earthquakes or flooding, the basic principles of preparedness apply to all types of hazards. For example, establishing an effective warning system is an essential measure for major disasters with a sudden onset. Moreover, coastal communities often face multiple, complex, and often interrelated natural disaster shocks (e.g., hurricanes often induce coastal flooding). Therefore, it is important that preparedness activities should have an "all hazard" focus while accounting for the more specific hazard attributes (Sutton and Tierney, 2006).

Second, preparedness efforts should be organized to support both response and recovery. While the traditional focus of preparedness is on response activities during and immediately after a disaster, increased emphasis is now placed on recovery preparedness (National Resource Council or NRC, 2006). This often involves gathering sources and materials necessary to aid in the repair and reconstruction of properties and infrastructure post disasters. Another type of recovery preparedness is the purchase of disaster insurance as a way to transfer risks and offset the *ex post* disaster losses (NRC, 2006).

Third, preparedness is often conflated with hazard mitigation because they both involve activities undertaken before disaster strikes to protect public safety and reduce risks. However, it should be noted that mitigation focuses on long-term measures that can prevent disasters and reduce the damage that results from those that occur. For example, mitigation typically includes building protective structures (e.g., seawalls, dams, and levees for protecting against the risk of flooding and storm surge in coastal areas, elevating homes) and non-structural measures (e.g., coastal zoning and land-use policy, building codes and regulations, and managed retreat from risky locations). By contrast, preparedness focuses more on improving the readiness of organizations and communities to respond to emergencies and provide more "active" protection than mitigation at the time a disaster strikes (Donahue and Joyce, 2001; NRC, 2006). Nonetheless, some activities may fall under the umbrella of both preparedness and mitigation, such as evacuation plans, warning systems, communication on disaster risks and public education (Sutton and Tierney, 2006).

Economic approaches have long been used to evaluate investments in disaster risk reduction and hazard mitigation. Many existing studies have employed benefit-cost analysis (BCA), which is a well-established method of analysis for comparing the benefits and costs of a given project that may span multiple years. A typical benefit-cost analysis involves identifying and monetizing the benefits and costs, discounting all future values, and calculating the net present value (NPV) or benefit-cost ratio (BCR) to inform relevant investment decisions.

In most disaster-related BCA studies, the benefits are measured in terms of avoided future damages. A common approach utilizes engineering-based probabilistic loss estimation models based on historical data and expert opinion to project the expected damage with and without specific mitigation measures in place; the difference, or avoided damages, is considered to be the benefit (Kousky et al. 2019; Davlasheridze et al. 2019). For example, a widely-cited study conducted by the Multihazard Mitigation Council (MMC, 2005) reported an average BCR of 4:1, or an overall net benefit of \$10.5 billion, in its assessment of 5,479 FEMA hazard mitigation projects between 1993 and 2003 for earthquakes, flooding, and wind hazards. Its estimated BCR varies from 1.5 for earthquake mitigation and 5.1 for flood mitigation.

The MMC study 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), direct and indirect economic losses (e.g., business interruption).[1] For some of the benefits involving non-market goods (e.g., environmental and historic benefits), MMC (2005) used the benefit transfer approach by adapting previous estimates of valuation that are considered analogous. In 2017, the MMC expanded their 2005 study by using new data, assumptions, and the updated HAZUS-MH loss estimation models. Their 2017 study and most recent 2019 report indicate an average BCR of 6:1 for selected federal mitigation grants.

While most disaster-related BCA studies have suggested positive economic gains of risk reduction measures, their BCR estimates tend to vary significantly by hazard type, location, and type of mitigation measures and appear to be highly sensitive to specific assumptions, methodologies, and parameter choices (Moench et al.2007; Hawley et al. 2012; Shreve and Kelman, 2014; Mechler, 2016). For example, based on the same data used in MMC (2005), the Congressional Budget Office (CBO) employed different discounting and extrapolation methods and found a more conservative BCR of 3:1 for federally-funded mitigation projects.

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[1] The loss estimation modeling such as HAZUS-MH is typically composed of multiple independent modules, including the hazard module that estimates the likelihood and severity of a hazard, the exposure module that contains information on the population and capital stock at risk, and a vulnerability module that estimates the expected damage.

Two issues are important to underscore regarding the gaps in the existing literature. First, despite the growing body of BCA research on hazard mitigation, the literature about valuing preparedness is much more limited and inconsistent. As noted earlier, preparedness is distinct from mitigation in its goal and scope of activities. By far, the majority of the BCA studies have focused more on structural mitigation measures (or "hard resilience") rather than disaster preparedness and other non-structural measures or "soft resilience" (Mechler, 2016; Shreve and Kelman, 2014; Davlasheridze et al. 2019). Very few studies have examined the economic returns on preparedness investment exclusively and only within country-specific contexts (UNICEF, 2015).

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 hazard 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. Preparedness is essentially a dynamic process as opposed to the static nature of structural mitigation. 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; they may induce changes in individual behaviors (e.g., risk attitude and self-protective actions affected by public education and crisis communication) or enhance organizational structure and capabilities for response and coordination for emergencies. There is considerable uncertainty in these social outcomes and their actual influence on loss mitigation. Third, some of the societal benefits or co-benefits of preparedness activities, such as increased feelings of security, enhanced crime awareness, and environmental protection, remain difficult to quantify and monetize. All these challenges raise questions about the reliability of existing approaches and value estimates of preparedness.[2]

The second research gap relates to the lack of empirical studies examining the causal link between preparedness and disaster-related outcomes. Establishing this causal link is critical for the BCA to be valid; it provides greater confidence in determining the causal relationship between an intervention/treatment and a particular outcome (e.g., reduced disaster losses) or attributing the observed outcome to preparedness only but not the other factors. An ex-post analysis based on empirical data and causal inference (e.g., experimental or quasi-experimental methods, econometric modeling) is a useful approach for this purpose (Kousky et al. 2019). Yet such analysis is confounded by the counterfactual problem. From an evaluation point of view, it is difficult to know the effectiveness of preparedness in the absence of an actual disaster incident that tests these activities. When certain preparedness measures are already implemented, it is also difficult to know what would have been the impact of the disaster in the absence of these measures.

Only a handful of studies have been conducted to examine the loss reduction effect of hazard mitigation investment using empirical data. Most of these studies have used data on government disaster aid as a measure of public investments in emergency management. In the United States, the federal government plays a critical role in providing disaster assistance to state

[2] For example, MMC (2005) estimated a much lower BCR of 1.4:1 for most process grants that involve hazard planning. The report indicated that due to the lack of access to studies on process-related community planning activities, they had to heavily rely on the benefits transfer approach with extensive use of assumptions and prior estimates from other domains, which may introduce errors in their estimation (Kousky et al. 2019).

and local governments as well as private individuals, households and business particularly after a disaster occurs (Miao et al. 2018). Healy and Malhotra (2009) used panel data and econometric modeling to estimate the effect of federal disaster preparedness spending (measured in broad scope, also including mitigation projects) and relief aid spending on a county's actual disaster damages. Their analysis shows that preparedness spending can significantly reduce disaster damage while relief aid has little effect on loss mitigation. Based on their empirical findings, Healy and Malhotra (2009) estimated that a $1 increase in preparedness spending saves $15 in future disaster costs.

Also using econometric modeling, recent studies have examined the loss-reduction effect of disaster aid programs. Davlasheridze et al. (2017) examined the effects of different FEMA grant programs on hurricane-induced property losses in 651 U.S. counties along the Atlantic coast. They found that a 1% increase in cumulative pre-disaster mitigation spending would reduce property damage in the following year by 0.21%, whereas the same increase in post-disaster response and recovery spending only reduces future damage by 0.12%. Davlasheridze and Miao (2021a) examined the loss reduction effect of multiple federal post-disaster aid that provide assistance to state and local governments as well as households and private businesses.[3] They found that, among all, spending on low-interest disaster loans leads to the largest reduction in property damages from flooding. They also show that grants for public infrastructure restoration and flood control measures significantly reduce flood losses, whereas disaster relief aid given to private individuals has a limited effect on loss avoidance. In another recent study, Welsch et al. (2022) use a dynamic panel feedback model (accounting for the feedback of previous flood shocks in a random-effects model) to examine the loss reduction effect of flood mitigation funding from three major federal mitigation programs. They estimate that a 100% increase in mitigation spending reduces flood damages by approximately 9% in the next year, which translates into a wide range of $208,350 - $405,188 in total social benefits. In addition to the risk reduction efficacy of disaster aid, several studies have examined the aid effect on other socioeconomic outcomes including public housing provision (Davlasheridze and Miao, 2021b), business survival (Davlasheridze and Geylani, 2017) and flood insurance purchases (Davlasheridze and Miao, 2019). A more comprehensive review of the literature on disaster aid and their loss-reduction efficacy is provided in Davlasheridze and Miao (2021a) and Miao (2018).

Nonetheless, there is scant research specifically focused on the causal effects of preparedness. Several studies have examined exercises and drills, and provided evidence on their efficacy for improving preparedness knowledge and performances (Agboola et al. 2013; Skryabina et al. 2017). However, these studies did not relate their findings to loss mitigation and provided little information about the economic cost and benefits of conducting these activities. From this perspective, using disaster program aid expenditure data provides a unique advantage for evaluation purposes because the inputs are known and quantifiable (based on the reported grant amount and project costs), and their link with specific disaster outcomes can be analyzed through econometric modeling and regression analysis. Such data can also be used to identify different types of disaster-related projects (preparedness, mitigation, response, and recovery) and examine the pattern of their distribution (e.g., Miao and Davlasheridze, 2022).

[3] These include FEMA's Public Assistance, Individual and Household Assistance, Hazard Mitigation Grant programs, and the Small Business Administration's Disaster Loan Assistance.

### 3. Research Design: Data and Method

With a focus on government preparedness investments, we identify the disaster preparedness projects that are funded through multiple federal disaster grant programs, which are discussed in turn as below.

***a. Emergency Management Performance Grant (EMPG)***

The EMPG is a major disaster preparedness grant program administered by the Federal Emergency Management Agency (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 preparedness.[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 federal preparedness spending.

***b. Hazard Mitigation Assistance***

FEMA administers three major hazard mitigation programs including the Hazard Mitigation Grant Program (HMGP), Pre-Disaster Mitigation (PDM) Grant, and Flood Mitigation Assistance (FMA) Grant programs. 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, flood proof and retrofit, flood control structures, warning systems, hazard mitigation planning and risk assessment, and public education activities. Given our specific focus on preparedness, we categorize these funded projects into the preparedness or "soft resilience" (including planning, risk assessment, public education, warning system) and mitigation or "hard resilience" (e.g., property acquisition and demolition, structural elevation and retrofit, flood control infrastructure).

***c. Public Assistance***

As FEMA's largest disaster aid program, the Public Assistance (PA) program provides grants to state, local, and tribal governments following a PDD. The program funds immediate disaster response (e.g., debris removal, supplies necessary for emergency response) and permanent public works including restoration and repairs of damaged public infrastructure, flood control facilities and public buildings, and reconstruction of 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. While the projects related to emergency response are primarily used for the PDD incident that already occurred, some of the remaining resources and

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[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.

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 distinguish the two types of PA grants in our study.

**3.1 Data**

We collect data on disaster grants primarily from FEMA. We note that FEMA's data on EMPG only include projects that have been recently awarded since 2010. We combine this data set with the Census Bureau's Consolidated Federal Funds Report (CFFR) which reports the annual federal expenditures by programs prior to 2010. Yet, the vast majority of EMPG projects were funded after 2010.

It should be noted that, for all these FEMA programs, grants were provided to both state governments and county governments as well as other types of local governments such as municipalities and tribal governments. For smaller governments such as municipalities and tribes, we assign their received aid to the county where they are located. For grants received by state governments (for example, a large proportion of the EMPG grants was awarded to state emergency management agencies), we calculate the state-level aid per capita (using the statewide population) and add that to the county-level per capita aid. Note that for all these programs we measure a county's received aid per capita in a given year and then use a perpetual inventory model to construct the disaster aid stock, which is assumed to depend on a distributed lag of the current and past flows of disaster grants. We described the method in more detail in the model section.

We use the disaster loss data from the Spatial Hazards Events and Losses Database for the United States (SHELDUS). SHELDUS reports county-level estimates for property and crop losses as well as deaths and injuries caused by a variety of natural hazards including hurricanes, floods, earthquakes, droughts, wildfires, tornadoes, severe storms/thunderstorms, and winter weather (ice storms). 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).

SHELDUS is considered one of the largest and most reliable data sources for direct natural disaster damage in the U.S., although it has a number of limitations and particularly reporting bias. For example, 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. Gall et al. (2009) provide a comprehensive review of the common biases in disaster loss estimation across agencies including hazard bias (i.e., not all types of natural hazards are reported) as well as temporal and threshold biases. The reporting bias may add noise to the disaster damage variable in our data, but the improvement in data collection and reporting in recent years may help mitigate the temporal and threshold biases. Notably, our sample covers a more recent period when NWS has started reporting losses from smaller-scale disaster incidents. To construct our dependent variable, we calculate the annual damage from flood- and storm-related hazards (including floods, hurricanes, severe storms, surge events) that occurred in a county during a given year. Figure 1 presents the average flood- and storm-induced damage per capita by sample county from 1960 through 2019.

Disaster losses are heavily influenced by the physical magnitude of natural hazards. Therefore, it is critical that we control for the exogeneous shocks (as explanatory variables) to identify the effect of government investments on disaster losses. 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 (NCDC) Global Historical Climatology Network (GHCN), 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. Thus a positive value indicates excessive rainfall and possible flooding conditions in a county year. The main advantage of using NCDC's station-level weather monitoring data is to avoid self-reporting bias and we can exploit the exogenous variations in precipitation to measure the physical flooding conditions.[5]

As for hurricanes and tropical storms, we use the geospatial storm data from NOAA's International Best Track Archive for Climate Stewardship (IBTrACS)[6]. 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 (Category 1, Category 2, and Category 3 and higher) in a county-year observation. We also use the wind speed data from NOAA's storm event database to identify the count of gale events, storm wind events, and severe storm wind events in a county year.

It has been widely recognized that natural disasters losses are place-based and vary 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 (BEA). We also control for a county's annual poverty rates and median housing values using data from the U.S. 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).

### 3.2 Study Sample

Our study sample includes all the U.S. coastal states including the six states in the Great Lake region (AL, AK, CA, CT, DE, FL, GA, HI, IL, IN, LA, MA, ME, MD, MH, MI, MN, MS, NC, NJ, NY, OH, OR, RI, SC, TX, VA, WA, WI), given our specific research interest in coastal communities and coastal hazards. The unit of analysis is a county, and we compile a panel data set with all variables aggregated at the county level for each year over the period 2000-2019. Our

[5] 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.

[6] 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.

regression modeling uses a full sample (including all coastal states) and a confined sample of coastal watershed counties (based on NOAA's categorization). [7]

### 3.3 Empirical model

To identify the effect of government preparedness spending on disaster losses, we estimate a panel fixed effects model specified in equation (1) below:

$$(1)\quad \ln(Loss_{ct}) = X_{ct-1}\alpha + \ln(EMPG_{ct-1})\beta_1 + \ln(HMG_{ct-1})\beta_2 + \ln(PA_{ct-1})\beta_3 + Hazard_{ct}\beta_4 + \lambda_t + \lambda_c + \lambda_{region*t} + \varepsilon_{ct}$$

The dependent variable, $Loss_{ct}$, measures the property damage caused by flood- and storm-related disasters in county $c$ during a given year $t$. Our key variables of interest include the multiple federal disaster grant programs, including the EMPG, major hazard mitigation grant programs (denoted as HMG), and Public Assistance (denoted as PA). For HMG, we combine all project data from the three FEMA programs mentioned 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 primarily structural mitigation projects such as property acquisition and relocation, retrofit, stormwater management) 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 through year t-1. Specifically, we calculate the aid stock by program using the equation below:

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

$\rho$ is the rate of stock depreciation, which we assume to be 10 percent. 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.[8] The disaster loss and aid stock variables are all log-transformed, so we can interpret the estimated coefficients in the form of elasticity (in a log-log model specification).

In this model, we control for the physical magnitude of the contemporaneous disaster shock, denoted as *Hazard,* which contains multiple variables measuring a county's annual rainfall anomaly and number of storm or wind events of different scales. $X_{ct-1}$ corresponds to a vector of county-level socioeconomic and demographic variables, including per capita personal income (log transformed), size of population (log transformed), median housing values (log transformed), percentage of black (%) and poverty rates (%). All these variables are lagged by one year to

[7] According to NOAA's definition, the coastal watershed counties are those where land use and water quality changes most directly impact coastal ecosystems. The permanent U.S. population that resides in the Coastal Watershed counties can be thought of as "the population that most directly affects the coast." A county is considered a Coastal Watershed County if one of the following criteria is met: (1) at a minimum, 15 percent 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 percent of a coastal uses 8-digit cataloging unit.

[8] 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 our regression model.

mitigate the endogeneity problem. We also include the cumulative count of flood and storm PDDs a county has experienced in the past five years to account for its disaster experiences. $\lambda_t$ 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). $\lambda_c$ denotes the county fixed effects, which control for a country's time-invariant unobserved characteristics that may influence its disaster damage (e.g., the baseline flood risks such as special flood hazard areas, geography, disaster assistance received in earlier years). 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 in the same region (Atlantic, Gulf of Mexico, Pacific, Great Lakes). Finally, $\varepsilon_{ct}$ 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. All the data analysis and econometric modeling are performed using *Stata*. Table 1 reports the summary statistics of our main variables.

## 4. Results

Table 2 reports our estimation results from the baseline model (equation 1) using two different samples. Specifically, column 1 is based on the full sample including all counties in the U.S. coastal states, whereas column 2 is based on a confined sample of coastal watershed counties only. Given our research interest in coastal communities, we place more emphasis on the results using the confined sample. First of all, we find that almost all the disaster grant 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 one percent increase in the two aid (stock) variables is expected to reduce flood- and storm-related damages in the following year by 0.08 and 0.07 percent, 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 than the other disaster grants. One percent increase in the two aid variables would reduce disaster damage by 0.19 and 0.15 percent, respectively. These findings may suggest that communities at higher risk of flooding and storms are more efficient in using federal disaster aid for mitigating local disaster risks. This finding is also expected because disaster occurrence is more frequent in the high-risk areas, and the benefits (in terms of loss avoidance) of investments in disaster preparedness and mitigation tend to be higher in these regions.

As a robustness check, in column 3 we estimate our baseline model for coastal counties, using only disaster aid directly allocated to counties (as opposed to columns 1 and 2 in which we use the per capita aid received by both counties and states). Our estimates are largely consistent with the baseline findings in column 2, although the estimated coefficient on mitigation grants targeting preparedness projects is no longer statistically significant. The magnitude of both EMPG and PA grants' (emergency response related) effect is smaller than our estimates in column 2.

Across all specifications, we show that our 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 and wind event variables all increase with the hazard magnitude, which is also consistent with our expectations. Regarding the other control variables measuring county-level socioeconomic and demographic characteristics, we find that a county with a higher percentage of black populations tends to experience fewer property damages. One possible explanation is the racial minority variable may also correlate with the lack of or low valued property and assets and lower economic exposure to natural hazards. Also, damages on average are lower in coastal counties with larger populations, all else held constant. It should be noted that all these social control variables have less within-county variation than cross-country variation. Since we use a panel fixed effects model in this research, our estimates tend to be less efficient as our empirical approach mainly exploits the within-county variations.

***Extension: heterogeneous effects of preparedness investments by regions***

In addition to the baseline model, we undertake an extension to examine the heterogeneity of the effects of disaster grants by regions, since natural hazards are geographically dependent. We expect that the benefits of preparedness spending may vary across regions, and the same amount of preparedness or mitigation spending may yield higher values of damage reduction in places at higher risks of coastal hazards. Table 3 reports our estimation results using the baseline model (equation 1) for coastal counties only in the four regions (Atlantic, Gulf of Mexico, Pacific, Great Lakes) separately. Because hurricanes mostly occur in the Atlantic and Gulf coast regions, the hurricane variables are dropped from the regression for the other two regions (Pacific and Great Lakes states).

Our results show that the loss-mitigating effects of disaster grants are most prominent in the Gulf Coast region. Almost all the aid variables are statistically significant with the negative sign, except for PA grants targeting permanent works. The magnitude of these estimated coefficients is also larger compared to the estimates for other regions. This may suggest that our baseline average estimates of disaster aid's effects (presented in Table 2) are driven by the Gulf coast counties, and this is likely due to the region's higher propensity of exposure to coastal hazards and particularly hurricanes. We also find that EMPG exerts a statistically significant, negative effect on disaster damages in the coastal counties in Great Lake and Pacific states, whereas its effect is insignificant for the Atlantic region. The PA grants targeting emergency responses are found to reduce damages in coastal counties in the Atlantic and Gulf coast regions. The PA grants targeting permanent works has a negative effect (only marginally significant) on damages in the Great Lakes coastal counties, while mitigation grants (preparedness activities related) have a positive coefficient in the same specification. We are not exactly clear about what drives the positive effect of preparedness funding on disaster damages. One possible explanation is that the Great Lake region is not as prone to floods and storms as the Gulf and Atlantic regions and government spending on public preparedness or mitigation activities may crowd out private adaptation actions.

***Extension: impact of cumulative disaster aid in the past ten years***

Note that in our baseline model, we use the disaster aid stock variables that are constructed using the perpetual inventory model which places higher weight on more recently received disaster aid. This approach assumes that the economic value of disaster aid-funded projects depreciates over time. Nonetheless, it should be noted that many of these projects, especially involving public infrastructure, may take a longer time to be completed after federal aid is disbursed. Thus, depending on the type of disaster grants, they may have a delayed effect on loss mitigation and their mitigation efficacy may not necessarily decline over time. To further test for the temporal variations in aid's effect, we use an alternative measure by calculating the sum of disaster grants (by program) received by a county in the past ten 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 accounting for the potentially delayed effect of those structure-related projects.

Table 4 reports our estimation results using the full sample (all counties in the coastal states) and confined sample (coastal watershed counties only) separately. We show that all aid variables are statistically significant and exert a negative effect on disaster damages in both specifications. 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 higher loss-mitigating efficacy 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.

***Calculating the return on investments (ROI)***

Since we use a log-log model to estimate the aid effect, we interpret our estimated coefficients in the form of elasticity. This approach, however, makes it difficult to directly interpret the aid effect in dollar units and estimate the benefit-cost ratio of government investments in preparedness and mitigation. To infer returns on investment (i.e., return in terms of damage avoidance on a $1 spent on disaster preparedness grants), we combine our sample statistics with the estimated coefficients of different aid variables. Specifically, we use the median and mean values of unlogged disaster aid variables among counties with positive aid (i.e., including the nonzero values only) to gauge spending in dollars with one percent increase in disaster aid variables. We use the sample mean of unlogged disaster damages per county by year as the baseline to quantify the amount of damages in dollars given a one percent increase in the damage variable. We calculate the return on investment by multiplying aid coefficients with the sample average of disaster damage, which is divided by the sample statistics of disaster aid. Table 5 reports our estimates based on our regression results in Tables 2 and 4, where our regression sample differs across columns. As a robustness check, we also use the average flood damages for only county-years with positive disaster aid (a more restricted sample) as the baseline and re-estimate the returns on investment by aid program, which are reported in Table 6. Our estimates are highly similar to those in Table 5.

Overall, we find that the estimated ROIs are generally higher in coastal counties (columns 2, 3, and 4 in Tables and 6) compared to the estimates for all counties in coastal states (columns 1 and 4 ). This is because the loss-reduction effect (estimated coefficients from regression analysis) of disaster aid in coastal counties is larger in magnitude, and also the average flood damages are higher in these counties. We also note that, for all disaster aid programs, using the mean values of aid variables yields smaller ROI estimates than their median values. This is because the disaster aid data have a highly skewed distribution with larger means than medians. In this sense, an 1% increase based on sample means implies a larger increase in dollars of aid than using the median values, thereby driving down the estimated ROIs. Therefore, it is important to acknowledge that the estimated return on investment is sensitive to the choice of sample statistics.

Among different disaster aid programs, we show the EMPG grants and mitigation grants targeting the preparedness activities have relatively higher ROIs. This is presumably because the sample means and medians of these two variables are much smaller than the other three aid variables, and a one percent increase in the former translates into a relatively small amount of spending in dollars. Nonetheless, the larger ROIs of the EMPG program are also driven by its loss reduction effect suggested by our regression results (shown in Table 2-4). As we indicated earlier, the EMPG funding generally results in the largest loss-reduction effect compared to other disaster aid programs. One possible explanation could be related to the relative "transiency" of the different disaster programs examined here. Disaster assistance programs tied to PDDs can be thought to be "transitory" programs in the sense that they are only following large-scale shocks triggering PDDs. 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 continuity of existing programs (both mitigation and planning). Specifically, because of the reactive nature of PDD-related aid programs, they 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. For example, after undertaking the recovery programs provided through PA, communities could also apply for various mitigation programs (e.g., HMGP). Many of these localities are fiscally distressed (due to incurred recovery costs, depressed housing, population outmigration) in the aftermath of a disaster and may choose the type of mitigation projects that are easy to implement and maintain or even limit the extent of mitigation activities (e.g., number of buyout properties). Mismanagement of government-funded projects (Gelinas 2016) and inefficient use of funding for disaster risk management has been a common criticism of disaster aid programs (Kousky and Shabman 2017).

Second, aid programs such as EMPG allow communities to build organizational capacity in advance by developing contingency plans (e.g., immediate response evacuation and housing) and improving warning systems. Communities can also build capacity and set the stage for necessary strategic, operation and tactical post-disaster planning, and accelerate the delivery of resources, including preparing for post-disaster funding. Also important to note is that most of the programs supported by EMPG allow covering maintenance and sustainment costs for existing grants and funding for continuity planning to ensure continued functionality of vital public services (FEMA, 2021). Third, it is worth noting that compared to many 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 particular, Miao et al. (2021) apply the fiscal federalism theory to disaster mitigation and suggest that decentralizing disaster mitigation funding can lead to inefficient protection against flood-related disasters. Our results may, to some extent, resonate with the proposition and findings in the aforementioned study.

It should also be noted that counties generally do not experience flooding or storms every year, since disasters are triggered by the exogenous natural hazards that are relatively rare events. Moreover, the tendency to experience damage varies spatially by place depending on geographic characteristics and other social and resilience factors. There is also significant variation across the country in the distribution of federal disaster aid and related assistance. While in this subsection we provide a range of estimated ROIs in dollars, the ROIs should be subject to locations; in other words, one dollar spending on preparedness and mitigation should in theory result in higher returns on investment or avoided damage in higher-risk regions. In this context, our regression estimates of loss reduction effect (in the percentage term) can be particularly useful if they are integrated with local average disaster damages and disaster aid or expenditures in a specific locality to generate more meaningful ROI estimates. Lastly, it is important to note that our analysis is based on historical weather and disaster damages data. As climate change is changing the pattern of local precipitation and likely makes extreme weather events more frequent and intense (IPCC, 2012), our ROI on disaster mitigation and preparedness could be underestimated. It is crucial that the ROIs account for the projected future climate risks at the locality level.

## 5. Conclusion

In this research, we empirically examine the effect of multiple federal disaster aid programs on reducing subsequent flood-related damages across U.S. coastal states, with a particular focus on government preparedness expenditures. Our empirical analysis draws on panel data of nearly 2,000 counties over the years 2000-2019 and estimates a fixed effects model that controls for the unobserved cross-county heterogeneity and other time-varying socioeconomic and demographic attributes. Our analysis distinguishes different types of aid programs and aid targeting different functions, including preparedness (emergency management), mitigation (soft resilience/preparedness vs. hard resilience/structural mitigation), response (emergency protective measures) and recovery (permanent works). This study is the first to account for the differences among aid programs and funded projects (particularly the difference between preparedness and mitigation) and also the first to explicitly examine the resilience implications of disaster aid for coastal communities.

Our results show that disaster aid generally helps reduce subsequent flood-related property damage at the county level, while 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 flood damages: a one percent increase in the cumulative aid stock causes a 0.08 percent decrease in damages across U.S. coastal states and reduces the damages in coastal counties by 0.19 percent. The Public Assistance grants supporting emergency response are also found to yield a strong loss reduction effect: a one percent increase in the aid is expected to reduce subsequent flood damage by 0.07-0.15 percent. In terms of regional heterogeneity, we show that the impacts of disaster aid are stronger in coastal counties compared to non-coastal counties, and are most prominent in the Gulf Coast region. To put these estimated coefficients into perspective, we use the sample statistics of disaster aid and damages variables to estimate the return on government investment in disaster management. We estimate that one dollar spent on the EMPG program generates economic returns, in the form of avoided damage, with a range of 3-5 dollars on average and even higher in coastal counties, of 14-27 dollars. The mitigation grants targeting preparedness and soft resilience activities yields returns, with a wider range, of 1-7 dollars on average and 5 - 32 dollars in coastal counties. We do note that the estimated return on investment is sensitive to the choice of sample statistics used for making such inferences.

It is important to note that, in this research, we take an ex-post approach to estimate the link between government investments (e.g., in preparedness and mitigation) and observed disaster damages to infer the economic value of disaster preparedness. This approach is different from the engineering-based probabilistic loss estimation models and places more emphasis on causal inference using empirical data. Another approach for estimating the benefits of non-market goods and the provision of public services (such as preparedness and mitigation) is to elicit the average individual willingness to pay (WTP) for such goods using contingent valuation (CV) surveys. For example, a recent study by Wehde et al. (2021) employs a CV approach to estimate the public WTP for a weather app that provides continuously updated probabilistic hazard information. They estimate that the mean WTP for this good is 7.53 per person, which is converted into an estimated value of $901 million - $1.56 billion using the total U.S. population. Nonetheless, the CV approach is based on people's stated preferences and commonly suffers from the hypothetical bias, where respondents tend to report WTP higher than their actual WTP because the situation is unrealistic (Champ and Bishop 2001).

Similarly, a report recently released by the U.S. Council of the International Association of Emergency Managers (IAEM-USA) and the National Emergency Management (NEMA) estimated that the return on one-dollar per capita spending from EMPG exceeds $700 million. Their estimates were based on a survey of over 1,000 state and local emergency management agencies, yet details about their evaluation methodology were missing and may lack methodological rigor.[9] One direction for future research is to combine surveys and observational data. 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, training) at the locality level. Such data could be combined with disaster damages to analyze the loss reduction effect of specific preparedness activities and spending through regression analysis. It is also important for future research to compare these empirical estimates derived from the ex-post approach with estimates based on CV and WTP surveys on similar preparedness activities. Lastly, it should also be noted that this study focuses on government-funded public disaster projects and community preparedness, while preparedness also includes a variety of activities carried out by individuals and households. More future research should seek to provide more empirical evidence on the loss reduction effect of private preparedness behaviors.

[9] This report was retrieved from https://www.nemaweb.org/index.php/resources/#reportsandpubs

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## Table 1. Summary Statistics of Main Variables

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| **full sample (obs = 37,620)** | | | | |
| property damages (log) | .7982871 | 1.404633 | 0 | 12.76145 |
| EMPG grants (log) | .2978479 | .6693359 | 0 | 6.474397 |
| Mitigation grants - Preparedness (log) | | .9319426 | 0 | 7.753869 |
| Mitigation grants - structural mitigation (log) | 1.511439 | 1.567755 | 0 | 10.05298 |
| Public Assistance - emergency response (log) | 2.608414 | 1.769105 | 0 | 11.19918 |
| Public Assistance - permanent works (log) | 2.996488 | 1.889138 | 0 | 11.07708 |
| Rainfall anomaly | .2590553 | 1.20953 | -6.824703 | 8.99921 |
| # of hurricanes (category 1) | .0009835 | .032183 | 0 | 2 |
| # of hurricanes (category 2) | .000319 | .0192886 | 0 | 2 |
| # of hurricanes (category 3+) | .0002127 | .0145813 | 0 | 1 |
| # of gale events | .3650452 | .4814492 | 0 | 1 |
| # of storm wind events | .2909888 | .4542244 | 0 | 1 |
| # of severe storm wind events | .046757 | .2111208 | 0 | 1 |
| # of flood & storm PDDs in past 5 years | 1.787507 | 1.655963 | 0 | 11 |
| Personal income per capita (log) | 10.58655 | .2373323 | 9.633583 | 12.19038 |
| Population (log) | 10.68735 | 1.405251 | 5.556828 | 16.12861 |
| Median housing values (log) | 11.85785 | .4877896 | 9.940042 | 14.22313 |
| Poverty rates (%) | 15.33351 | 6.342459 | 2.5 | 49.3 |
| Percentage of African American (%) | 12.67335 | 16.61089 | 0 | 86.73226 |
| **Sample of coastal counties (obs = 12,522)** | | | | |

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| property damages (log) | .831541 | 1.580116 | 0 | 12.76145 |
| EMPG grants (log) | .317272 | .6900183 | 0 | 4.557687 |
| Mitigation grants - Preparedness (log) | .8228282 | .9284854 | 0 | 7.304007 |
| Mitigation grants - structural mitigation (log) | 1.721937 | 1.64612 | .0074201 | 10.05298 |
| Public Assistance - emergency response (log) | 2.753419 | 2.038244 | 0 | 11.19918 |
| Public Assistance - permanent works (log) | 2.972854 | 2.101494 | 0 | 11.07708 |
| Rainfall anomaly | .2567537 | 1.172772 | -4.700679 | 8.325779 |
| # of hurricanes (category 1) | .0022361 | .0488976 | 0 | 2 |
| # of hurricanes (category 2) | .0008785 | .03221 | 0 | 2 |
| # of hurricanes (category 3+) | .0003993 | .0199792 | 0 | 1 |
| # of gale events | .3947452 | .4888154 | 0 | 1 |
| # of storm wind events | .2464463 | .4309586 | 0 | 1 |
| # of severe storm wind events | .0452803 | .2079266 | 0 | 1 |
| # of flood & storm PDDs in past 5 years | 2.111164 | 1.87317 | 0 | 11 |
| Personal income per capita (log) | 10.65628 | .2768079 | 9.633583 | 12.19038 |
| Population (log) | 11.21224 | 1.481592 | 6.001415 | 16.12861 |
| Median housing values (log) | 12.08427 | .5390579 | 10.32514 | 14.22313 |
| Poverty rates (%) | 14.53977 | 6.181121 | 2.5 | 45.7 |
| Percentage of African American (%) | 14.04959 | 15.57114 | 0 | 79.61105 |

**Table 2. Modeling Impact of Disaster Grants on Damages**

| | (1) | (2) | (3) |
|---|---|---|---|
| EMPG grants (log) | -0.0754*** | -0.189*** | -0.0968*** |
| | (0.0221) | (0.0364) | (0.0357) |
| Mitigation grants - Preparedness (log) | -0.0277* | -0.0580** | -0.0374 |
| | (0.0147) | (0.0259) | (0.0246) |
| Mitigation grants - structural mitigation (log) | -0.0263** | -0.0491*** | -0.0560*** |
| | (0.0112) | (0.0185) | (0.0167) |
| Public Assistance - emergency response (log) | -0.0657*** | -0.147*** | -0.132*** |
| | (0.0150) | (0.0270) | (0.0221) |
| Public Assistance - permanent works (log) | -0.0288** | -0.0233 | -0.0305* |
| | (0.0126) | (0.0224) | (0.0184) |
| Rainfall anomaly | 0.293*** | 0.294*** | 0.290*** |
| | (0.00945) | (0.0190) | (0.0191) |
| # of hurricanes (category 1) | 2.383*** | 1.948*** | 1.920*** |
| | (0.513) | (0.537) | (0.544) |
| # of hurricanes (category 2) | 2.553*** | 1.977* | 1.933* |
| | (0.965) | (1.045) | (1.049) |
| # of hurricanes (category 3+) | 6.614*** | 7.504*** | 7.462*** |
| | (1.526) | (0.579) | (0.564) |
| # of gale events | 0.280*** | 0.295*** | 0.300*** |
| | (0.0258) | (0.0494) | (0.0492) |
| # of storm wind events | 0.356*** | 0.332*** | 0.330*** |
| | (0.0266) | (0.0544) | (0.0545) |
| # of severe storm wind events | 0.515*** | 0.393*** | 0.391*** |
| | (0.0441) | (0.0897) | (0.0898) |
| # of flood & storm PDDs in past 5 years | -0.000370 | 0.0219** | 0.0172 |
| | (0.00660) | (0.0111) | (0.0108) |
| Personal income per capita (log) | -0.0805 | -0.463 | -0.741** |
| | (0.138) | (0.292) | (0.296) |
| Population (log) | -0.231 | -0.716** | -0.556* |
| | (0.150) | (0.300) | (0.289) |
| Median Housing values (log) | -0.0478 | 0.235 | 0.292* |
| | (0.107) | (0.171) | (0.173) |
| Poverty rates (%) | -0.00567 | -0.0163* | -0.0155 |
| | (0.00476) | (0.00986) | (0.00988) |
| Percentage of African American (%) | -0.0200** | -0.0324** | -0.0380** |
| | (0.00856) | (0.0162) | (0.0161) |
| Constant | 4.605* | 11.45** | 12.01** |
| | (2.359) | (4.953) | (4.905) |
| Observations | 37,620 | 12,522 | 12,522 |
| Number of counties | 1,883 | 627 | 627 |

Notes: All the specifications include county FE, year FE and region by year FE. Column 1 includes all counties in U.S. coastal states, and column 2 and 3 includes coastal counties only. Standard errors are clustered by county.
$*$p<0.1; $**$p<0.05; $***$p<0.01

**Table 3 Modeling Impact of Disaster Grants on Damages by Region**

| | Lake | Atlantic | Gulf | Pacific |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| EMPG grants (log) | -0.149*** | -0.0704 | -0.521*** | -0.172** |
| | (0.0542) | (0.0588) | (0.159) | (0.0834) |
| Mitigation grants - Preparedness (log) | 0.0930** | 0.00914 | -0.148*** | -0.0555 |
| | (0.0448) | (0.0356) | (0.0536) | (0.0600) |
| Mitigation grants - structural mitigation (log) | -0.0156 | -0.0297 | -0.0829** | -0.0323 |
| | (0.0199) | (0.0263) | (0.0408) | (0.0539) |
| Public Assistance - emergency response (log) | -0.0111 | -0.159*** | -0.203*** | -0.0189 |
| | (0.0445) | (0.0347) | (0.0586) | (0.0790) |
| Public Assistance - permanent works (log) | -0.0476* | 0.0218 | -0.0533 | -0.0449 |
| | (0.0279) | (0.0276) | (0.0548) | (0.0693) |
| Rainfall anomaly | 0.249*** | 0.333*** | 0.417*** | 0.118** |
| | (0.0237) | (0.0240) | (0.0553) | (0.0452) |
| # of hurricanes (category 1) | | 1.911** | 1.534*** | |
| | | (0.814) | (0.543) | |
| # of hurricanes (category 2) | | 1.237 | 2.305** | |
| | | (1.730) | (1.016) | |
| # of hurricanes (category 3+) | | 6.480*** | 7.272*** | |
| | | (1.728) | (0.576) | |
| # of gale events | 0.357*** | 0.255*** | 0.301** | 0.262*** |
| | (0.0702) | (0.0696) | (0.125) | (0.0961) |
| # of storm wind events | 0.435*** | 0.245*** | 0.269** | 0.438*** |
| | (0.0633) | (0.0884) | (0.130) | (0.140) |
| # of severe storm wind events | 0.595*** | 0.451*** | 0.158 | 0.499*** |
| | (0.141) | (0.156) | (0.177) | (0.185) |
| # of flood & storm PDDs in past 5 years | 0.0372* | 0.00169 | -0.0168 | 0.0186 |
| | (0.0191) | (0.0119) | (0.0297) | (0.0445) |
| Personal income per capita (log) | -0.0465 | -0.793* | 0.176 | -0.395 |
| | (0.505) | (0.472) | (0.520) | (0.550) |
| Population (log) | -1.266* | -1.150*** | -0.254 | 0.571 |
| | (0.668) | (0.378) | (0.420) | (0.716) |
| Median Housing values (log) | 0.311 | 0.118 | -0.929** | 0.0244 |
| | (0.321) | (0.220) | (0.468) | (0.445) |
| Poverty rates (%) | -0.0112 | -0.0445*** | -0.00622 | 1.40e-05 |
| | (0.0152) | (0.0139) | (0.0218) | (0.0286) |
| Percentage of African American (%) | 0.00703 | -0.0180 | -0.0555* | 0.00856 |
| | (0.0308) | (0.0149) | (0.0290) | (0.0611) |
| Constant | 11.79 | 21.72*** | 14.71 | -2.196 |
| | (9.847) | (7.304) | (10.30) | (13.47) |
| Observations | 3,760 | 6,059 | 2,759 | 1,483 |
| Number of counties | 188 | 303 | 138 | 75 |

Notes: All the specifications include county FE and year FE. Standard errors are clustered by county. ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

**Table 4. Modeling Impact of Disaster Grants (ten-year cumulative flows)**

| | (1) | (2) |
|---|---|---|
| EMPG grants (log) | -0.0835*** | -0.186*** |
| | (0.0212) | (0.0356) |
| Mitigation grants - Preparedness (log) | -0.0252** | -0.0459** |
| | (0.0125) | (0.0220) |
| Mitigation grants - structural mitigation (log) | -0.0204*** | -0.0335** |
| | (0.00790) | (0.0152) |
| Public Assistance - emergency response (log) | -0.0512*** | -0.0827*** |
| | (0.0125) | (0.0228) |
| Public Assistance - permanent works (log) | -0.0238** | -0.0466** |
| | (0.0116) | (0.0210) |
| Rainfall anomaly | 0.294*** | 0.294*** |
| | (0.00946) | (0.0191) |
| # of hurricanes (category 1) | 2.374*** | 1.948*** |
| | (0.511) | (0.533) |
| # of hurricanes (category 2) | 2.572*** | 2.011* |
| | (0.963) | (1.046) |
| # of hurricanes (category 3+) | 6.610*** | 7.544*** |
| | (1.549) | (0.582) |
| # of gale events | 0.279*** | 0.292*** |
| | (0.0259) | (0.0494) |
| # of storm wind events | 0.356*** | 0.330*** |
| | (0.0266) | (0.0545) |
| # of severe storm wind events | 0.506*** | 0.388*** |
| | (0.0440) | (0.0881) |
| # of flood & storm PDDs in past 5 years | -0.00386 | 0.0144 |
| | (0.00637) | (0.0105) |
| Personal income per capita (log) | -0.112 | -0.482 |
| | (0.138) | (0.296) |
| Population (log) | -0.212 | -0.620** |
| | (0.152) | (0.307) |
| Median housing values (log) | -0.0295 | 0.268 |
| | (0.107) | (0.170) |
| Poverty rates (%) | -0.00511 | -0.0133 |
| | (0.00478) | (0.01000) |
| Percentage of African American (%) | -0.0209** | -0.0348** |
| | (0.00870) | (0.0168) |
| Constant | 4.538* | 10.17** |
| | (2.377) | (5.052) |
| Observations | 37,681 | 12,564 |
| Number of counties | 1,890 | 633 |

Notes: All the specifications include county FE, year FE and region by year FE. Column 1 includes all counties in U.S. coastal states, and column 2 includes coastal counties only. ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

**Table 5 Estimated Returns on $1 Spending on Disaster Aid**

| *Corresponding coefficients* | Table 2 column 1 | Table 2 column 2 | Table 2 column 3 | Table 4 column 1 | Table 4 column 2 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Based on mean values (nonzero obs)** | | | | | |
| EMPG Grants | -2.659 | -13.997 | -7.448 | -2.527 | -5.683 |
| Mitigation Grants - preparedness | -1.126 | -5.156 | (-2.106) | -0.732 | -2.878 |
| Mitigation Grants - structural mitigation | -0.177 | -0.507 | -0.341 | -0.114 | -0.284 |
| PA - emergency response | -0.122 | -0.282 | -0.234 | -0.063 | -0.118 |
| PA - permanent works | -0.033 | (-0.029) | -0.046 | -0.020 | -0.043 |
| | | | | | |
| **Based on median values (nonzero obs)** | | | | | |
| EMPG Grants | -4.810 | -27.200 | -15.761 | -4.522 | -10.149 |
| Mitigation Grants - preparedness | -7.442 | -32.001 | (-7.470) | -5.947 | -6.201 |
| Mitigation Grants - structural mitigation | -2.787 | -6.131 | -1.897 | -2.403 | -4.502 |
| PA - emergency response | -0.877 | -3.370 | -2.894 | -0.587 | -1.570 |
| PA - permanent works | -0.240 | (-0.411) | -1.263 | -0.171 | -0.702 |

Notes: Numbers in parentheses are derived from the estimated coefficients that are statistically insignificant.

**Table 6. Estimated Returns on $1 Spending on Disaster Aid ((based on the sample average damage for county-year with positive aid)**

| *Corresponding coefficients* | Table 2 column 1 | Table 2 column 2 | Table 2 column 3 | Table 4 column 1 | Table 4 column 2 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Based on mean values (nonzero obs)** | | | | | |
| EMPG Grants | -3.341 | -14.412 | -7.867 | -2.658 | -5.818 |
| Mitigation Grants - preparedness | -1.145 | -5.207 | (-1.902) | -0.747 | -2.916 |
| Mitigation Grants - structural mitigation | -0.177 | -0.507 | -0.284 | -0.114 | -0.284 |
| PA - emergency response | -0.126 | -0.296 | -0.310 | -0.065 | -0.124 |
| PA - permanent works | -0.034 | (-0.031) | -0.065 | -0.021 | -0.045 |
| **Based on median values (nonzero obs)** | | | | | |
| EMPG Grants | -6.044 | -28.005 | -16.648 | -4.757 | -10.390 |
| Mitigation Grants - preparedness | -7.563 | -32.315 | (-6.747) | -6.075 | -6.282 |
| Mitigation Grants - structural mitigation | -2.788 | -6.131 | -1.577 | -2.407 | -4.501 |
| PA - emergency response | -0.909 | -3.534 | -3.844 | -0.610 | -1.645 |
| PA - permanent works | -0.249 | (-0.432) | -1.791 | -0.178 | -0.738 |

Notes: Numbers in parentheses are derived from the estimated coefficients that are statistically insignificant.

**Figure 1 Average per capita property damage from floods and storms (in 2015 dollars) over 1960-2019**