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ORIGINAL ARTICLE

Assessing social equity of federal disaster aid distribution: A nationwide analysis

Qing Miao[1] | **Meri Davlasheridze**[2] | **Allison C. Reilly**[3]

[1]Rochester Institute of Technology, Rochester, Texas, USA

[2]Department of Marine and Coastal Environmental Science, Texas A&M University at Galveston, Galveston, Texas, USA

[3]Department of Civil and Environmental Engineering, University of Maryland, College Park, Maryland, USA

Correspondence
Qing Miao, Department of Public Policy, Rochester Institute of Technology, George Eastman Hall 1327, 1 Lomb Memorial Drive, Rochester, NY 14623, USA.
Email: qxmgla@rit.edu

Abstract
In this study, we conduct the first comprehensive, nationwide assessment of social equity performance of multiple federal post- and pre-disaster assistance programs that differ in targeted recipients, project types, forms of aid, and funding requirements. We draw on the social equity and distributive justice theory to develop and test a set of hypotheses on the influence of program design and specificity on their aid distributional patterns and equity performance. The analysis uses panel data of about 3000 US counties to examine the relationship between a county's receipt of federal assistance and its recent disaster damage, socioeconomic, demographic, political, local government, and geographic characteristics in a two-stage random effects Tobit model. Expectedly, we find that post-disaster grants are largely driven by recent disaster damage, while damage is simultaneously influenced by local socioeconomic conditions. For all disaster programs, disproportionately more federal aid is allocated to populous counties. For programs geared toward state and local governments and targeting community recovery and mitigation, more aid is received by counties with better socioeconomic conditions. Conversely, for programs targeting individual relief and recovery, more aid is given to counties with lower incomes and greater social vulnerability. Results also indicate that counties located in high-risk regions receive greater outlays. These findings shed light on the varying degrees of social equity of federal disaster assistance programs tied to their cost-share requirement, funding caps, and inherent complexity of application procedures.

KEYWORDS
distributive justice, federal disaster aid, local governments, natural hazards, social equity

1 | INTRODUCTION

The US federal government has a history of providing financial aid to assist local governments and communities in preparing for, mitigating, responding to, and recovering from natural hazards. Federal disaster aid is critical for addressing the uneven hazard exposure and impacts nationwide, and disparities in the ability to cope with disasters. Yet, as major disasters become more frequent and more federal disaster funds are dispersed (Pew, 2020), increased concerns have been raised about whether disaster aid has been distributed equitably (GAO, 2021). Researchers noted that the current disaster policy primarily focuses on recovery and restoring wealth and property to pre-disaster levels, which results in disproportionately fewer resources being allocated to those economically and socially disadvantaged groups (Fothergill & Peek, 2004; Howell & Elliott, 2019; Muñoz & Tate, 2016; Peacock et al., 2014; Raker, 2023). Recent studies have empirically examined the distribution of federal disaster aid, indicating disparities among different demographic groups (Domingue & Emrich, 2019; Drakes et al., 2021; Emrich et al., 2020, 2022; Entress et al., 2023; Han et al., 2024; Tyler et al., 2023).[1] As existing research has mostly focused on individual federal aid programs, a systematic approach is lacking but needed to assess the distributional pattern of various disaster programs and elucidate how their program designs may contribute to inequitable aid allocation.

[1] In addition to the US-based research, there is a separate line of literature examining the link between natural disasters and international aid flows (e.g., Becerra et al. 2014; Yang, 2008) and exploring factors influencing the allocation of international disaster assistance such as political considerations, media coverage, and recipient countries' institutional capacity (Easterly & Pfuytze, 2008; Eisensee & Strömberg, 2007; Drury et al., 2005; Olsen et al., 2003).

In this study, we investigate the factors influencing the allocation of federal disaster assistance to counties and whether more such aid is directed to counties with more socially vulnerable populations who are in greater need of assistance. Specifically, we provide the first comprehensive, nationwide analysis of six major federal disaster aid programs and unpack whether preference in aid delivery is given to particular regions and demographics. These six aid programs target different phases of emergency management (preparedness, mitigation, response, and recovery) and differ in their aims and recipients, program design, forms of assistance, and type of funded projects. For these programs, we examine how their aid distributional patterns and social correlates differ depending on their program design and attributes to shed light on their social equity performance.

We begin by conceptualizing the notion of social equity within our research context. As a guiding principle in public policy and administration, social equity is a multifaceted concept concerning justice and fairness in terms of treatment, service provision, opportunity, decision-making procedures, and distribution of substantive benefits and costs (Collins & Gerber, 2006; 2008; Cooper, 2004; Frederickson, 1990; Guy & McCandless, 2012). Specifically concerning resource distribution, the notion of equity is distinguished from strict equality but often implies material inequalities based on the Rawlsian theory of distributive justice postulating that the greatest benefits should be provided to the least advantaged members in society (Rawls, 1971). Within disaster management, the concept of social equity is closely linked to social vulnerability, as it has been long recognized that natural hazards have heterogenous effects on various groups due to their different levels of vulnerability and resiliency shaped by sociodemographic characteristics (Verchick, 2012; Emrich et al., 2020; Rivera & Knox, 2022). For instance, the low-income and minority populations tend to be more vulnerable to hazards with fewer resources and limited capacity for preparedness and recovery (Cutter & Emrich, 2006; Cutter et al., 2003). Thereby, from an equity perspective, more government assistance should be provided to socially vulnerable groups to reduce their hazard exposure and assist them through recovery. Nonetheless, serving the vulnerable and ensuring social equity in disaster assistance can be complicated and challenging for at least two reasons.

First, the current federal disaster policy links the need for aid directly with sustained disaster damage. Notably, the majority of federal disaster aid is disbursed in the aftermath of a disaster through the Presidential Disaster Declaration process. This policy approach raises concerns as scholars argue that disaster relief aid privileges asset owners and areas of high investment and disadvantages renters, unhoused people, and public housing occupants who have fewer assets and are in greater need of aid (Peacock et al., 2014; Howell and Elliott, 2019, Domingue & Emrich, 2019; Emrich et al., 2020, 2022). These vulnerable groups often experience greater disruptions from hazards, but their economic exposure is comparatively low and does not necessarily trigger more monetary losses than the wealthier groups.

The second problem arises from the observation that social needs for aid are often inversely related to the capacity to obtain aid (Hall, 2008), leading to unequal access to federal disaster assistance. Experiencing similar levels of disaster damage, vulnerable groups are less likely to apply for and receive federal aid because they may have limited capabilities or inadequate knowledge or information to navigate the aid application process (Domingue & Emrich, 2019; Raker, 2023; Tyler et al., 2023). Their local governments may lack the organizational capacity and fiscal resources to apply for federal funds due to complex application procedures and the cost-sharing requirement for many assistance programs, especially after disasters strike (Comfort et al., 2010; Domingue & Emrich, 2019).[2] Conversely, higher capacity jurisdictions tend to focus heavily on the procurement of federal resources and often have a better chance of doing so successfully (G. Brody et al., 2010; Smith et al., 2013).

Despite the significance of the problem and long-standing recognition of social vulnerability, the existing scholarship on disaster aid and whether they meet the need of the vulnerable is limited. Recent studies examined the correlation between disaster aid outlays and various social vulnerability indicators, but mostly confined to a specific disaster program, post-disaster recovery funds, or particular geographic locations (Domingue & Emrich, 2019; Drakes et al., 2021; Emrich et al., 2020, 2022; Entress et al., 2023; Raker, 2023). Our study contributes to the existing literature in three ways. First, by taking a more holistic and systematic approach to assessing social equity of federal disaster aid allocation among multiple pre- and post-disaster assistance programs with different attributes (e.g., targeted recipients and funding requirements). This enables us to make cross-comparison among programs and understand, for the first time, how program design influences the pattern of disaster aid allocation and social equity performance. This is also the first nationwide study of this kind that tracks major federal disaster outlays across about 3000 counties in the past two decades to paint a comprehensive picture of the distributional pattern.

Second, unlike prior research that primarily examines the sociodemographic correlates of disaster aid (Domingue & Emrich, 2019; Drakes et al., 2021; Emrich et al., 2020; Han et al., 2024), we focus on elucidating the allocation of federal disaster aid by incorporating additional factors including local fiscal resources, political leanings, and geographic risks, all of which shape a locality's inclination to access and acquire disaster grants. Moreover, we develop an integrated conceptual model in which disaster damage is an intermediate factor that drives federal aid allocation while also being influenced by social vulnerability and other community characteristics. By doing this, we disentangle separate mechanisms that influence the receipt of disaster aid either

[2] One example, discussed in a recent Government Accountability Office report (GAO, 2022a), is that many low-income school districts are denied funding or receive less funding than needed from FEMA's disaster recovery programs. This is because districts must adequately document their building conditions to prove that damage was caused by the disaster, while many poor districts often do not have sufficient staff to maintain the necessary records and thus fail to meet FEMA's requirements (GAO, 2022a).

directly or indirectly through disaster damage and also examine the social disparities in both disaster damage and aid distribution.

Lastly, our empirical analysis focuses on disaster damage and federal aid induced by flooding, severe storms, and hurricanes. This focus carries important economic and policy relevance, as hurricanes and flooding are the costliest weather disasters in the United States and are expected to be more intense as a result of climate change (Miao et al., 2018; Wing et al., 2020). While hurricanes mainly occur in the coastal areas (e.g., Atlantic and Gulf states), severe storms and flooding are the most prevalent hazards across the United States, accounting for the majority of the nation's presidential declared disasters. Based on our conceptual model, we treat damage as endogenous and use hazard magnitude measures derived from precipitation and wind speed data to instrument for flood- and storm-induced damage in a two-stage model. This approach allows us to examine the social correlates of disaster damage and also obtain unbiased estimates of the disaster effect on federal aid. The latter is particularly important for tracking government spending on disasters, evaluating policy responsiveness, and projecting future fiscal exposure.

2 | POLICY CONTEXT AND CONCEPTUAL MODEL

The existing US federal disaster policy framework was established by the 1988 Robert T. Stafford Disaster Relief and Emergency Assistance Act (i.e., the Stafford Act). Under the Stafford Act, the president is authorized to declare a major disaster or emergency (known as a Presidential Disaster Declaration or a PDD), upon requests of a governor, for jurisdictions for which the impacts exceed a locality's capacity to respond.[3] The PDD, typically made at the county level, allows federal aid to be distributed through various disaster programs to state and local governments, and at times, affected households and businesses as well. From 2005 through 2019, the federal government spent over \$460 billion on disaster assistance (Pew, 2020), and about \$200 billion was disbursed through the Disaster Relief Fund (DRF), the primary source of federal disaster relief aid administered by the Federal Emergency Management Agency (FEMA) (Congressional Research Service, 2020). The vast majority of federal disaster aid is provided after a disaster or PDD to support post-disaster response and recovery. This grant process has been criticized for its reactive nature, political motivation, mismanagement of public funding, and less emphasis on pre-disaster mitigation and preparedness (Garrett & Sobel, 2003; Gasper & Revees, 2011; Healy & Malhotra, 2009; Kousky & Shabman, 2017; Schneider & Kunze, 2023). The receipt of federal disaster aid highly correlates with disaster losses (Domingue & Emrich, 2019; Drakes et al., 2021); the latter are often place-based and influenced by local socioeconomic and institutional capacity (Cutter & Emrich, 2006; Cutter et al., 2003).

To understand the factors and mechanisms that influence federal disaster aid outlays, we propose a conceptual model shown in Figure 1. We posit that federal disaster aid, especially from programs contingent on PDDs, is highly driven by reported disaster damage. Even for pre-disaster grants not contingent on PDDs, we expect that communities experiencing disasters recently are more likely to apply for such aid to fund risk-mitigation projects because of heightened risk perception (Miao and Davlasheridze, 2022). Thus, disaster damage is a critical factor that positively influences federal aid that flows from both pre-disaster and post-disaster assistance programs. In the meantime, disaster damage is determined jointly by the physical intensity of a hazard (an exogenous shock triggered by natural forces such as heavy precipitation leading to flooding) and the vulnerability of the affected population. Stronger shocks are associated with more damage, and thus the relationship is expected to be positive. We capture local vulnerability through a multitude of measures on a county's socioeconomic, demographic, local government, and geographic risk characteristics. However, the relationship between these attributes and damage, and these attributes and aid are uncertain. Because more vulnerable populations generally have fewer resources to invest in mitigation and are less capable of responding to and recovering from disasters, they tend to bear a heavier brunt and greater disruptions and damage from these shocks. Yet, the same groups of people have lower economic exposure in terms of property and assets that could be potentially destroyed by disasters. Therefore, whether socially vulnerable populations experience greater disaster-induced damage is an empirical question whose answer is likely hazard-location specific.

Furthermore, we posit that the same set of social factors influencing disaster damage can directly impact access to federal grants, as vulnerable communities often face more challenges in competing for and obtaining federal assistance. Previous research shows that socially disadvantaged groups are less likely to apply for disaster aid due to limited capacity in terms of language, knowledge, social connectedness, and familiarity with local public officials (Peacock & Girard, 1997; Tierney et al., 2001; Tyler et al., 2023). Moreover, because many federal disaster grants have specific funding requirements (e.g., state and local governments need to share the cost of eligible projects), many local governments with inadequate fiscal resources are unable to afford the nonfederal match and fail to apply. Nonetheless, it is noteworthy that federal agencies' funding decisions also account for other factors including social vulnerability, although its weight in the decision-making process is ambiguous due to high levels of discretion exercised by agencies (Congressional Research Service, 2017).

[3] Before a PDD is made by the president, FEMA evaluates the magnitude of damage caused by a hazard and a jurisdiction's need for federal assistance through the Preliminary Damage Assessment (PDA) process. FEMA uses the PDA information and per capita impact thresholds to provide a recommendation to the president concerning whether a major disaster declaration is warranted (CRS, 2017).

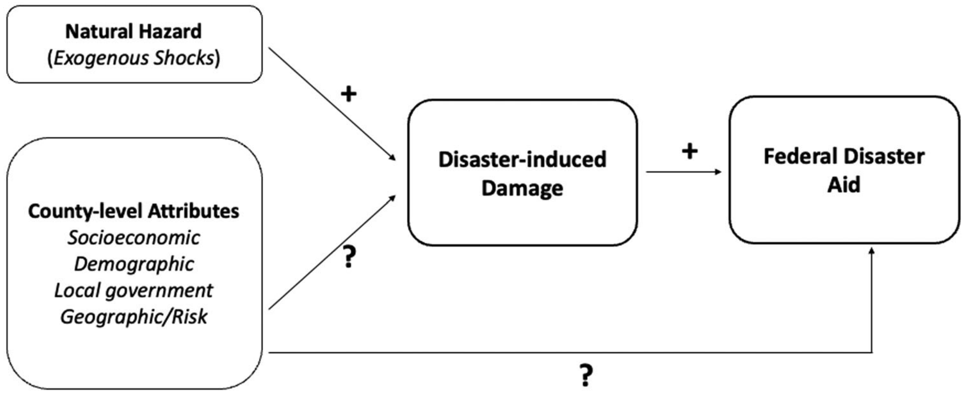

FIGURE 1 Conceptual model.

3 | DISASTER PROGRAMS AND DESIGN

This study examines six major federal disaster assistance programs that differ in aims, design, cost-share requirements, recipient stakeholders, and the type of funded projects, with key features summarized in Table 1. We begin with four major FEMA programs that provide grants to public entities (primarily state, local, tribal, and territorial governments). As FEMA's largest disaster aid program, the Public Assistance (PA) program provides grants following a PDD to fund immediate disaster response (e.g., debris removal, emergency response supplies) and permanent public works including restoration of damaged public infrastructure such as flood control facilities (Brown & Richardson, 2015). Also contingent on PDD designations, FEMA's Hazard Mitigation Grant Program (HMGP) funds long-term hazard mitigation projects that aim at reducing disaster risks ex ante (e.g., acquisition and relocation of properties in hazard-prone areas, retrofitting and building mitigation infrastructure, stormwater management). In addition to HMGP, FEMA also administers two additional hazard mitigation assistance programs, the Flood Mitigation Assistance (FMA) and Pre-disaster Mitigation (PDM) grant, neither of which require PDD designations.

We also include two disaster aid programs that target private entities including individuals, households, and business owners. FEMA's Individuals and Households Program (IHP) provides financial assistance and/or direct services to disaster-affected households and individuals with uninsured or under-insured necessary expenses. Notably, the IHP does not compensate for all disaster-induced losses but rather aims to support survivors' basic needs. The program also provides housing assistance that can be used to rebuild, replace, or repair the primary residence or to provide short-term housing accommodations (Congressional Research Service, 2019).[4] Another outlay through which the federal government supports private stakeholders is the Disaster Loan Assistance (DLA) program administered by the Small Business Administration (SBA). The DLA offers low-interest loans (at subsidized rates) with a fixed 30-year term to homeowners, renters, businesses, and private nongovernmental organizations and requires collateral (Congressional Research Service, 2019). Both DLA and IHP provide recovery funds contingent on PDDs, and the two programs also overlap in the application process and eligibility. Applicants typically apply for IHP first and may be directed to apply for DLA if they want to restore their home to its pre-disaster condition or if their income surpasses the minimum threshold for IHP aid (Congressional Research Service, 2019).

Regarding program designs, these aid programs vary in their application requirements, funding sources, and project sizes. We conjecture that specific program designs for aid distribution affect the program's social equity performance, with allocation considered more equitable if more aid is directed toward more vulnerable communities. First, disaster programs mainly targeting public entities generally fund projects on a cost-share basis, with the federal government paying for at least 75% of total project eligible expenses and the remainder paid by state and local governments. In contrast, no cost-share requirement exists in the administration of disaster assistance programs targeting private entities. We hypothesize that *the cost-share requirement for disaster projects limits aid to localities with greater social vulnerability and fewer resources*. Since this requirement imposes a high burden on administrative capacity and fiscal resources, less affluent communities may struggle to afford the local cost-share or to manage large-scale projects. The cost-share requirement can particularly result in highly inequitable outcomes in mitigation grants because mitigation is often a lower priority in disadvantaged communities (S. Anderson, Plantinga, et al., 2020).

Second, PDD-related recovery programs (including PA, IHP, and DLA) do not have a program-level funding cap, as their funds are primarily drawn from DRF and Congress' ad hoc supplemental appropriations (Congressional Research Service, 2020; Donahue & Joyce, 2001). The funding for HMGP has been capped at 15% of all FEMA's grant expenditures, excluding administrative costs (McCarthy, 2011). The FMA and PDM are both funded through annual appropriations and thus have total funding limits (Carter et al.,

[4] These funds may be used to make the house safe to live in; they may not be used to restore the home to its original state.

TABLE 1 Major federal disaster assistance programs.

Program	Public Assistance (PA)	Hazard Mitigation Grant Program (HMGP)	Flood Mitigation Assistance (FMA)	Pre-Disaster Mitigation Grant (PDM)	Individuals and Households Program (IHP)	Disaster Loan Assistance (DLA)
Agency	FEMA	FEMA	FEMA	FEMA	FEMA	SBA
Type of assistance	Grant	Grant	Grant	Grant	Grant	Loan (the current rates are 1.75% for borrowers without other loans and 3.5% for those who have credit elsewhere)
PDD required	✓	✓			✓	✓
Recipients	State and local governments Tribes and US territories (PA is also available to certain non-profit organizations)				Individuals, households (homeowners and renters)	Homeowners businesses
Project type	Response and recovery	Mitigation	Mitigation	Mitigation	Relief and recovery	Relief and recovery
	Emergency response (debris removal and clean-up) Permanent work (restoration and repairs of damaged public infrastructure)	Property acquisition and relocation; Retrofits (elevation, floodproof) and structural mitigation projects (stormwater management facilities; retention and detention basins; dams, dikes, levees, seawalls) Mitigation planning, training, education activities			Housing and rental assistance (uninsured loss, housing accommodations) Repairing household items and furnishing	Repairing and replacing assets, machinery, equipment, inventory and other expenses
Mitigation plans	✓	✓	✓	✓		
Benefit and cost ratio analysis		✓	✓	✓		
Relations to the National Flood Insurance Program (NFIP)			✓ Funds are limited to NFIP participating communities		✓ Qualified recipients are required to purchase and maintain flood insurance if they live in FEMA's designated 100-year floodplain	
Program funding limits	N/A	Max 15%	Limits set annually (2020: $150 million)	Limits set annually (2020: $500 millions)	N/A	N/A
Cost-share requirement—Federal share	75%	75%	75%+	75%+		
Individual project types and limits	No cap on individual projects (varying in size)				The IHP-funded housing assistance is capped $36,000 (in 2021)	$200,000 + 20% (property) $40,000 (content) $2 million + 20% (business)

Abbreviations: FEMA, Federal Emergency Management Agency; N/A, not available; PDD, Presidential Disaster Declaration.

2019).[5] The funding limits can intensify competition for grant applications for these mitigation programs and disadvantage communities and local governments with lower capacities in the aid application process. Therefore, we expect that *disaster programs with yearly funding caps provide less aid to localities with more vulnerable populations*.

Third, we expect disaster aid for government recipients (i.e., PA, HMGP, FMA, and PDM) to have poorer social equity performance compared to disaster aid for private agents (IHP and DLA). Not only do these aid programs for government recipients require cost shares, but the application procedures are also more complex, often requiring technical analysis and collaboration among multiple agencies and governments at different levels. Specifically, all four disaster grant programs targeting public entities require state and local governments to have mitigation plans as a precondition for application (Carter et al., 2019). To apply for mitigation funds, applicants should include additional cost–benefit analyses of their proposed project. In contrast, applications for IHP or DLA do not involve a cost-share requirement and are more simplified (mostly requiring evidence of damage). Furthermore, unlike the aid programs for governments, programs targeting private recipients impose funding caps for individual applications and projects.[6] The project-level cap can, to some extent, prevent these programs from over-subsidizing affluent individuals.

Several recent studies have examined the aid distribution of various federal programs, including PA (Domingue & Emrich, 2019), IHP (Drakes et al., 2021; Emrich et al., 2020, 2022), SBA loans (Emrich et al., 2020), and FMA (Tyler et al., 2023). With a focus on the social vulnerability factors, these studies present mixed findings. Drakes et al. (2021) show that IHP underserves renters because of its low outlays for this group that are also unrelated with disaster damage, but Emrich et al. (2020) find that IHP aid was distributed to places with higher damage and more renters. Domingue and Emrich (2019) find that social vulnerability has both positive and negative correlations with disaster aid depending on the indicators used. While many of these studies suggest that federal disaster aid programs underserve communities with more socially vulnerable populations, they have not fully accounted for the integrative impact of other factors on disaster aid including local government capacity, fiscal resources, and political influence, despite prior research evidence demonstrating their importance (Brody et al., 2010; Garrett & Sobel, 2003; Gasper & Reeves, 2011; Hall, 2008; Healy & Malhotra, 2009). More importantly, none of these studies has conducted cross-program comparisons or investigated the role of program design in their aid allocation patterns.

[5] For instance, FMA is operated using revenues collected by the National Flood Insurance Program (NFIP), with its funding restricted to NFIP participating communities (Carter et al., 2019).

[6] Specifically, the IHP-funded housing assistance is capped and adjusted annually with the maximum project grant set at $36,000 in 2021, though the typical grant size ranges between $1700 and $4200 (GAO, 2020b). For DLA, homeowners are eligible to borrow up to $200,000 as a result of damage to their properties and $40,000 for any damage to interior contents, while business entities can borrow up to $2 million to replace or repair real estate, inventory, and other property (CRS, 2019; GAO, 2020b).

4 | DATA

The data used in this study are compiled from various sources. First, federal grant and loan data for each disaster assistance program (i.e., PA, HMGP, FMA, PDM, IHP, and DLA) were retrieved from FEMA and SBA's open-source databases. Because PDDs are typically made at the county level, we use counties as our unit of analysis and aggregate the project-level federal spending in the raw data for each county-year observation by program. Given our focus on flood and storm hazards, we include only federal funds/loans related to these disaster events for the post-disaster assistance programs (based on information provided on each PDD). For pre-disaster assistance programs (i.e., FMA and PDM), we use all funded projects because FMA is exclusively for flood mitigation and the majority of PDM-funded projects are related to mitigating risks of flooding and storms.

Figure 2 displays the total federal disaster aid of our interest, distributed nationwide through the five FEMA programs and SBA's DLA, respectively, by year from 2000 through 2019 (in 2015 dollars). The 2005 spike is mainly driven by Hurricane Katrina, which is among the costliest disasters in US history. Figure 3 displays the breakdown of these grant funds by programs and shows that the PDD-related recovery funds (from PA, IHP, and DLA) account for the vast majority of the national total, while the share of mitigation aid (HMGP, FMA, and PDM) accounts for less than 10%.

Table 2 lists the independent variables used in this study with their data sources. We choose these variables drawing upon our conceptual model and relevant literature on the determinants of disaster aid allocation. The disaster damage data (related to flooding and storms) were obtained from the Spatial Hazards Events and Losses Database for the United States (SHELDUS). SHELDUS reports county-level estimates for deaths, injuries, and monetary losses caused by hazard, with its loss estimates for meteorological and hydrological events drawn from National Centers for Environmental Information's (NCEI) Storm Data and Unusual Weather Phenomena. For our research interest, we identified the annual county-level damage from floods, hurricanes, and severe storms only. Figure 4 shows the cumulative disaster damage per capita by county over 2000–2019. The damage are particularly concentrated in the Gulf Coast areas because the region is particularly prone to frequent hurricanes and storm surge. We also map the spatial distribution of FEMA aid and SBA's disaster loans across counties (reported in the Supporting Information Appendix), which exhibits a pattern highly similar to disaster damage. A sample mean test (reported in the Supporting Information Appendix) shows that lower income counties have experienced more flood- and storm-related PDDs by count and also are at higher flooding and storm risks, but their reported cumulative damage is not significantly different from those in their wealthier counterparts.

One thing important to note is that disaster damage data commonly suffer from reporting bias. Specifically, one limitation of SHELDUS is averaging disaster losses from an event

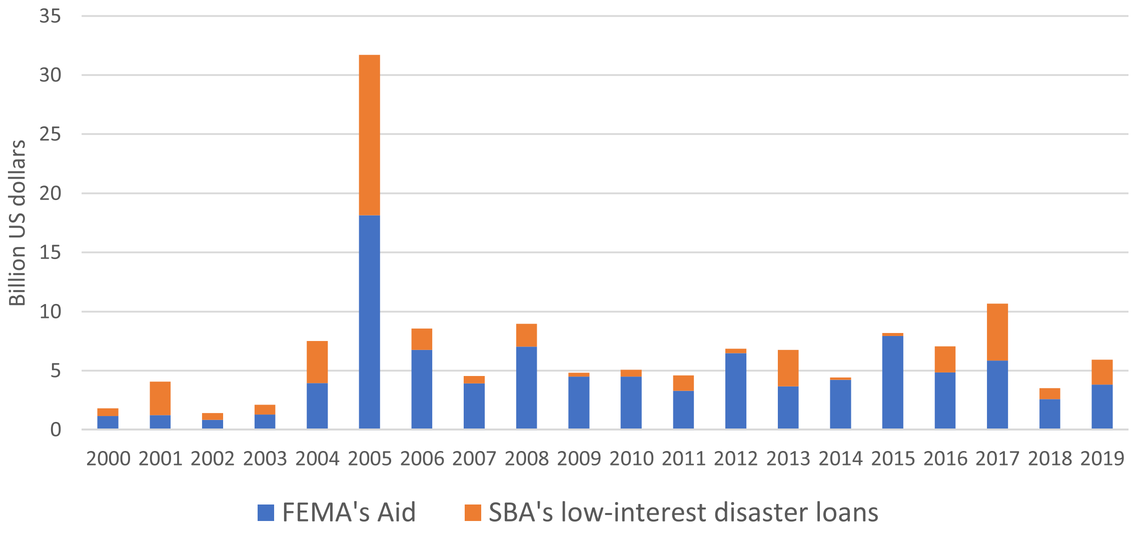

FIGURE 2 Annual Federal Disaster Aid (in billions) from the Federal Emergency Management Agency (FEMA) and Small Business Administration (SBA) programs over 2000–2019. *Note:* This figure only includes the flood- and storm-related disaster aid from the six disaster programs we examined in this study and does not account for disaster assistance from other hazards or other federal programs.

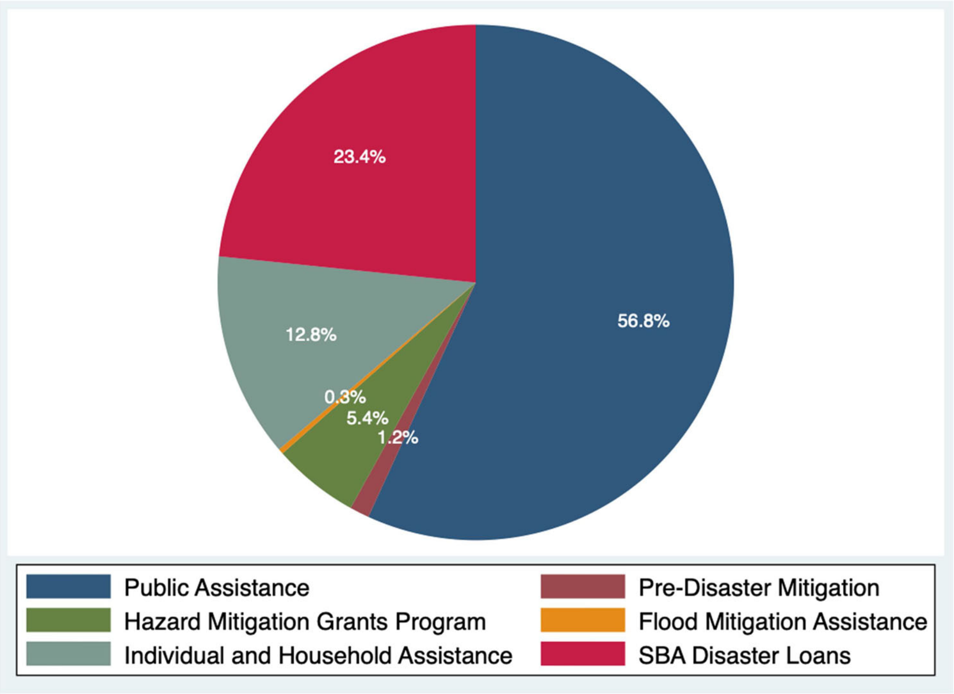

FIGURE 3 Breakdown of federal disaster aid by program (2000–2019). *Note:* This figure only includes the flood- and storm-related disaster aid from the programs we examined in this study and does not account for disaster assistance from other hazards or other federal programs.

across affected counties. In addition to imprecise measurement, disaster damage is also endogenous because it can be influenced by a community's socioeconomic conditions. To address the endogeneity problem, we follow Miao and Popp (2014) to construct variables measuring the physical hazard magnitude to instrument for disaster losses. Specifically, we use the precipitation data from NCEI and construct a rainfall anomaly variable. This variable measures the proportional deviation of a county's precipitation in year t from its long-run average, with positive values indicating excessive rainfall and possible flooding conditions. As for hurricanes and tropical storms, we measured the maximum 10-m 1-min sustained wind speed at the county's population centroid using the Willoughby et al. (2006) hurricane wind speed model imbedded within B. Anderson, Schumacher, et al.'s (2020) and B. Anderson, Schumacher, et al.'s (2020) open-source R

TABLE 2 Independent variables and data sources.

Hazard-related variables	Sources	County-level attributes	Sources
Flood- and storm-induced damage	SHELDUS	Personal income per capita	Bureau of Economic analysis
Rainfall anomaly (proportional deviations of annual precipitation from long-term average annual level)	NCEI's Global Historical Climatology Network	Low education indicator** (20% + population without high degree degrees)	Census
# Hurricanes of Categories 1, 2, and 3+ based on storm tracks and wind speed data	NOAA's International Best Tract Archive for Climate Stewardship, B. Anderson, Schumacher, et al.'s (2020) and B. Anderson, Schumacher, et al.'s (2020) open-source R package "hurricaneexposure"	Urbanization status (urban, metro, rural indicators)**	Census
Coastal county indicator*	NOAA	Median housing values**	Census
% 100-year floodplain*	FEMA—National Flood Hazard Layer and Census	% Renters**	Census
Historical hurricane exposure*	Zandbergen (2009)	Poverty rates	Census
		% African Americans	National Center for Health Statistics
		% Hispanic populations	National Center for Health Statistics
		Population	Bureau of Economic Analysis
		County land area*	Census
		County government own-source revenues per capita**	Census
		% Democratic voters	The Atlas of US Presidential Elections
		Swing county × presidential election year	The Atlas of US Presidential Elections

Note: Variables with * are time-invariant. Variables with ** contain interpolated values from the decennial census data. As for the own-source revenue variable, because most US county governments report their financial data to census every 5 years, we linearly interpolated the values for the missing years.
Abbreviations: FEMA, Federal Emergency Management Agency; NCEI, National Centers for Environmental Information; NOAA, National Oceanic and Atmospheric Administration; SHELDUS, Spatial Hazards Events and Losses Database for the United States.

package "hurricaneexposure." The script inputs the NOAA's National Hurricane Center's 6-h best track for each hurricane and then uses the Willoughby model—a parametric wind field model—downscale the best track to any geo-coordinate. We used the calculated wind speed data to identify storm magnitudes based on the Saffir–Simpson Hurricane Wind Scale and then calculate the count of hurricanes of different categories (Category 1, Category 2, and Category 3, and higher).[7]

In addition to the hazard intensity measures, we also control for a county's time-invariant geographic attributes related to its baseline flood or storm risks. These characteristics are measured by a binary indicator of coastal watershed county based on NOAA's classification[8], the ratio of a county's 100-year floodplain (FEMA designated special flood hazard area) to its total land area, and long-term hurricane/tropical storm exposure using the scores developed by Zandbergen (2009) based on the historical record of storm tracks for the period 1851–2003. We also include the total land area to control for a county's size.

To capture a community's socioeconomic and demographic characteristics, we use a variety of variables measuring county-level personal income per capita, median housing values, a binary indicator of lower educational attainment (i.e., more than 20% of the population without a high school degree according to the criteria used by the US Department of Agriculture), population size, percentage of African American populations, percentage of Hispanic populations, and percentage of renters (with their data sources listed in Table 2). To differentiate counties based on their urbanization status, we include three binary variables measuring an urban, metropolitan, or rural county using the USDA Rural-

[7] We did not use wind speed data directly as an instrument for damage because many counties in our national sample are not prone to hurricanes and have never been hit by one. However, we cannot assume the maximum wind speeds for these counties should be always zero, as they may still experience severe storms with high winds. Conceptually, their maximum wind speed should be treated as missing rather than zero. Our approach to avoid missing values (for wind speed) is to use the number of hurricanes of different categories as a measure of hazard magnitude. This measure is indirectly based on the wind speed and still captures the exogenous destructive power of a hurricane event. It also avoids making inappropriate assumptions of zero maximum wind speed in counties not affected by hurricanes.

[8] Data are retrieved from https://coast.noaa.gov/data/digitalcoast/pdf/defining-coastal-counties.pdf.

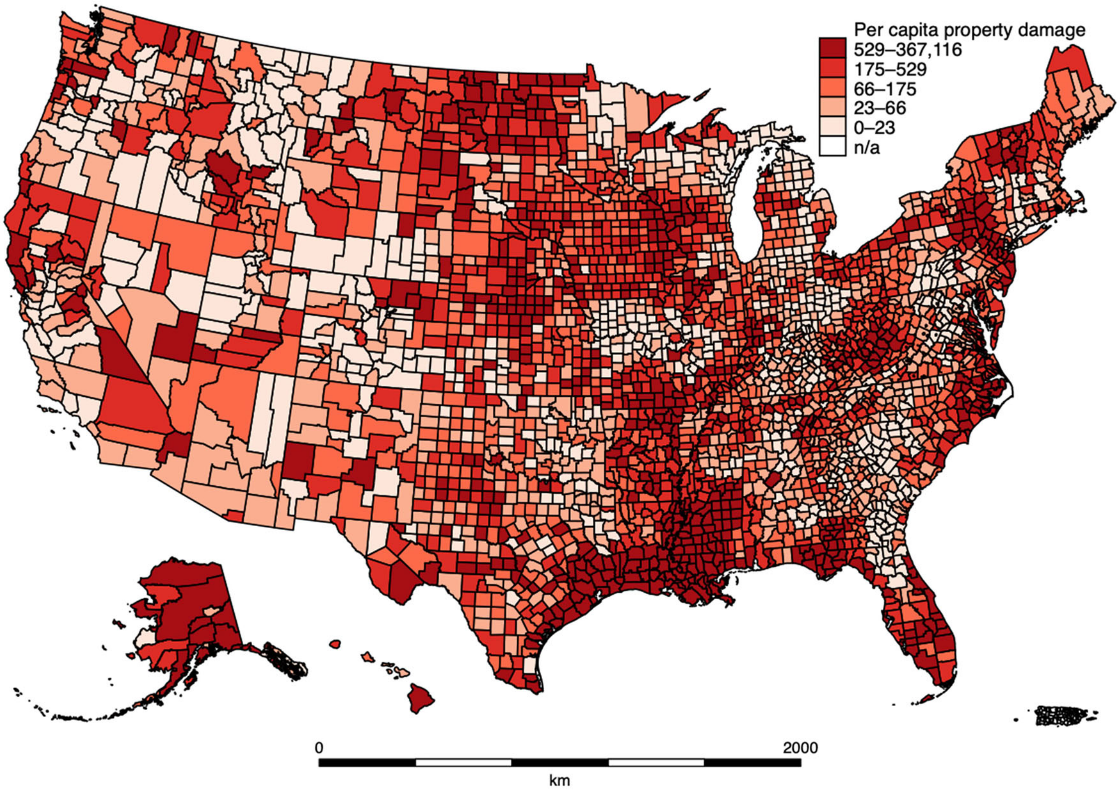

FIGURE 4 Cumulative flood- and storm-related damage by US county 2000–2019. *Note:* The disaster damage data were obtained from the Spatial Hazards Events and Losses Database for the United States (SHELDUS). The damage are in dollars (adjusted in 2015 price). The intervals correspond to quintile values of the damage distribution.

Urban Continuum Codes data. To measure a county's local government capacity and financial condition, we use a county government's own-resource revenues per capita based on the Census Bureau's State and Local Government Finance data. Data were interpolated in instances where only decennial census data are available.

Lastly, we control for a county's political leaning, which can influence federal disaster aid distribution through multiple channels. From the perspective of the federal government as an aid distributor (supply side), elected officials may direct more aid to jurisdictions that are politically important to them (Garrett & Sobel, 2003). To account for this channel of political influence, we follow Kousky et al. (2018) and create a swing county indicator for counties located in a swing state (Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania, Virginia, and Wisconsin) and also with the winning margin in the previous presidential election of less than 5%. We interacted the swing county variable with a presidential election year indicator, assuming that the effect of distributive politics is most prominent during election years. To control for local political leaning and ideology that may influence public support of government interventions in disaster management (Botzen et al., 2016; Wehde & Nowlin, 2021), we include a variable measuring the percentage of population voting for a Democratic candidate in the presidential election most recent to the disaster, with the data retrieved from Dave Leip's Atlas of US Presidential Elections.

Finally, our nationwide sample includes about 3000 US counties over the years from 2000 through 2019.[9] This timeframe is chosen because the data for most disaster assistance programs we examined are available post 2000. All these counties in our sample have either reported damage from flooding or storms or received at least one flood- or storm-related PDD over the study period. Table 3 reports the summary statistics of main variables.

5 | METHODS

To model the distribution of federal disaster aid outlays, we measure our dependent variable Aid_{ctp} using per capita disaster aid that county c received in year t from a given aid program p. For most counties and for most years, Aid_{ctp} is zero. We apply an inverse hyperbolic sine transformation (*asinh* hence forth) which allows us to interpret the coefficient in percent terms while retaining the zero-valued observations. Because the aid variable takes on the value of zero with positive probability and is continuous on its positive values, we

[9] For our analysis of PDM and IHP, the panel length spans from 2001 to 2019 and from 2022 to 2019, respectively, reflecting the availability of disaster aid data during those periods.

TABLE 3 Summary statistics of main variables.

	Mean	Standard deviation	Min	Max
Disaster variables				
Damage per capita (asinh transformed) (USD/capita)	0.841	1.402	0	12.761
Damage per capita (USD/capita)	65.756	2303.661	0	348,518.5
Rainfall anomaly (Unitless)	0.249	1.194	−6.824	8.999
# of hurricanes (category 1) (Count)	0.0018	0.0448	0	2
# of hurricanes (category 2) (Count)	0.0004	0.0196	0	1
# of hurricanes (category 3+) (Count)	0.0002	0.0153	0	1
Disaster aid variables				
PA aid per capita (asinh) (USD/capita)	0.713	1.669	0	11.446
PA aid per capita (USD/capita)	12.996	259.788	0	46,747.2
HMGP aid per capita (asinh) (USD/capita)	0.210	0.819	0	10.088
HMGP aid per capita (USD/capita)	1.940	48.809	0	10,663.83
FMA aid per capita (asinh) (USD/capita)	0.020	0.225	0	6.346
FMA aid per capita (USD/capita)	0.077	1.899	0	247.784
PDM aid per capita (asinh) (USD/capita)	0.055	0.3815	0	7.550
PDM aid per capita (USD/capita)	0.289	6.792	0	717.251
IHP aid per capita (asinh) (USD/capita)	0.2466392	0.953	0	9.524
IHP aid per capita (USD/capita)	3.419318	53.297	0	5160.497
IHP aid (homeowners) per capita (asinh) (USD/capita)	0.234	0.914	0	8.989
IHP aid (homeowners) per capita (USD/capita)	2.670	36.517	0	3022.007
IHP aid (renters) per capita (asinh) (USD/capita)	0.104	0.539	0	8.766
IHP aid (renters) per capita (USD/capita)	0.720	19.150	0	2419.088
DLA loans per capita (asinh) (USD/capita)	0.335	1.073	0	10.795
DLA loans per capita (USD/capita)	5.680	134.438	0	18,390.210
DLA loans (homeowners) per capita (asinh) (USD/capita)	0.271	0.9584	0	10.631
DLA loans (homeowners) per capita (USD/capita)	4.069	107.198	0	15,619.52
DLA loans (business) per capita (asinh) (USD/capita)	0.171	0.733	0	8.902
DLA loans (business) per capita (USD/capita)	1.611	32.318	0	2777.771
Other independent variables				
Personal income per capita (log)* (USD/capita)	10.552	0.232	9.476	12.028
Population (log)* (Count)	10.240	1.417	5.557	16.128
Poverty rates* (%)	15.361	6.203	1.7	62
Median housing values (log)* (USD)	11.740	0.460	9.940	13.935
Lower education indicator (binary)* (1/0)	0.351	0.477	0	1
Percentage of African American * (%)	8.576	14.237	0	86.732
Percentage of Hispanic (%)	7.762	13.080	0	97.783
Percentage of renters * (%)	26.191	6.945	8.666	74.920
Metropolitan (binary)* (1/0)	0.2458	0.431	0	1
Urban (binary)* (1/0)	0.476	0.499	0	1
Own-source revenues per capita (log)* (USD/capita)	7.249	0.8662249	−8.432	11.572
Democratic votes * (%)	38.867	13.191	3.145	92.457
Swing county* × election year (binary) (1/0)	0.011	0.105	0	1
County area (log)** (Square miles)	22.039	0.723	18.717	25.369

(Continues)

TABLE 3 (Continued)

	Mean	Standard deviation	Min	Max
Ratio of 100-year flood zone** (%)	10.247	13.206	0	100
Hurricane exposure** (Unitless)	4.272	11.717	0	78.558
Coastal county (binary)** (1/0)	0.189	0.392	0	1

Note: N = 59,742. Variables with * are lagged by 2 years when included in the model and their summary statistics reflect the lagged values. Variables with ** are time-invariant by county.

Abbreviations: DLA, Disaster Loan Assistance; FMA, Flood Mitigation Assistance; HMGP, Hazard Mitigation Grant Program; IHP, Individuals and Households Program; PA, Public Assistance; PDM, Pre-disaster Mitigation.

estimate a panel Tobit model that allows for censoring of the limited dependent variable (Equation 1). The latent aid variable, Aid^*_{ct}, is specified as a function of disaster damage (denoted as D_{ct}), a county's socioeconomic and demographic attributes, fiscal capacity and political leaning (denoted as the vector X_{ct}), and county-level time-invariant geographic variables capturing local flooding and storm risks (denoted as F_c). With regard to disaster damage, we consider the contemporaneous damage in year t and lagged values in years t-1 and t-2 to account for the near-term disaster effect. The delayed effect of past disasters could be because of the delay in both application and distribution of post-disaster aid. Moreover, recent experience with disasters may increase the interest in pre-disaster mitigation, and thus motivate counties to apply for additional aid. We also lag X_{ct} by 2 years to mitigate the potential confounding effects of lagged damage variables included in the same model.[10] We include year dummies (μ_t) to account for the yearly national shocks (e.g., disaster policy changes at the federal level) and state dummies (μ_{state}) that control for unobserved heterogeneity across states in their capacity to mitigate disaster risks and obtain federal funds.

$$Aid^*_{ctp} = X_{ct-2}\alpha + \sum_{i=0}^{2} D_{ct-i}\beta_i + F_c\gamma + \mu_t + \mu_{state} + \varepsilon_{ctp}. \tag{1}$$

The observed aid receipt variable is

$$Aid_{ctp} = \begin{cases} Aid^*_{ctp} & \text{if } Aid^*_{ctp} > 0 \\ 0 & \text{if } Aid^*_{ctp} \leq 0 \end{cases}, \tag{2}$$

$$\varepsilon_{ctp} = \mu_c + \eta_{ctp};\ \mu_c \sim N\left(0, \sigma^2_\mu\right);\ \eta_{ctp} \sim N\left(0, \sigma^2_\eta\right). \tag{3}$$

In this study, we use a random effects (RE) estimator obtained by maximum likelihood, assuming that the error term, ε_{ctp}, is composed of time-invariant county-specific random effects, μ_c, and an idiosyncratic error, η_{ctp}, that varies across counties and over time (Equation 3). There are several reasons why we use an RE model rather than fixed effects (FE) model. First, our study sample has a large N (about 3000 counties) and relatively smaller T (20 years). Using FE in the nonlinear Tobit model can pose the incidental parameters problem in maximum likelihood estimation and inconsistent FE estimates (Greene, 2003). Second, in the model, we include a set of time-invariant geographic variables to test whether more disaster aid is distributed to counties at higher risks of flooding or storms. Using county FE does not allow us to estimate the effect of these variables. Third, many of our independent variables (e.g., county-level socioeconomic and demographic characteristics) have less within-county variation than between-county variation. Since our research goal is to examine the distributional pattern of federal disaster aid among counties, the RE model allows us to exploit the cross-county variation to understand what makes certain counties receive more assistance than others. Moreover, as discussed in Kahn (2005), testing how within-region variations affect disaster outcomes is empirically difficult because these changes may not immediately translate into stronger or weaker local capacities to reduce hazard losses or to acquire federal funds, and there is likely a long latency between economic or demographic adjustments and observed disaster outcomes. Nonetheless, we note that the RE model relies on a stronger assumption that the county-specific effects (μ_c) are orthogonal to the covariates in the model, and we discuss its potential limitation in the conclusion.

As discussed above, disaster damage is endogenous because (1) damage is socially determined and there are unobservable factors that may simultaneously influence the impact of a disaster on a community as well as the community's tendency and ability to receive federal aid and (2) damage data have reporting bias and measurement error.[11] To address this problem, we employ a control function (CF) approach (Wooldridge, 2015) and estimate a two-stage model with instrumental variables (IVs) (see Equations 4 and 5). We use the physical magnitude measures of flooding and storms (rainfall anomalies and counts of hurricanes of Categories 1, 2, 3, and above) to instrument for damage because they reflect the exogeneous natural destructive power of a hazard that directly affects the amount of disaster damage and should

[10] To more accurately capture the political influence on aid distribution during election years, we interact the lagged swing county variable with the contemporaneous election indicator variables.

[11] In this case, reported damage is different from the true disaster-induced damage, and such error can affect the outcome variable as part of the error term.

only influence disaster aid through its effect on damage.

$$D_{ct} = X_{ct-2}\alpha + \sum_{i=0}^{2} Z_{ct}\delta_i + +F_c\zeta + \mu_t + \mu_{state} + \omega_{ct}, \quad (4)$$

$$Aid_{ctp} = X_{ct-2}\alpha + \sum_{i=0}^{2} D_{ct-i}\beta_i + \sum_{i=0}^{2} \hat{\omega}_{ct-i}\varphi_i + F_c\gamma + \mu_t + \mu_{state} + \varepsilon_{ctp}. \quad (5)$$

In the first stage (Equation 4), disaster damage per capita D_{ct} (also *asinh* transformed) is regressed on IVs (denoted by Z_{ct}) and other exogenous variables included in Equation (1). Since our baseline model (Equation 1) includes multiple endogenous variables (contemporaneous and lagged disaster damage), we instrument for damage using a distributed lag of IVs up to year *t*-2 accordingly. In the second stage of CF (Equation 5), we include the endogenous disaster damage variables, all other exogenous regressors, and $\hat{\omega}_{ct-i}$, which is the generalized residuals from the first-stage model which controls for unobserved factors (Vella, 1993; Vella & Verbeek, 1999). Since both Aid_{ctp} and D_{ct-i} are limited dependent variables with large numbers of zero-valued observations, we estimate the two stages (Equations 4 and 5) using the RE Tobit model.

6 | RESULTS

6.1 | First-stage results: Modeling disaster damage

Table 4 reports our results from the first-stage model where the dependent variable is per capita damage from floods and storms in a county-year. Because we use a distributed lag of disaster damage in our main model, we have multiple endogenous variables (damage in year *t*, *t*-1, and *t*-2), each of which has a separate first stage (reported in columns 1–3) and is regressed on a distributed lag of IVs (rainfall anomaly and hurricane counts in year *t*, *t*-1, and *t*-2) and the same set of social and geographic variables. For brevity, we report the estimates of hazard variables only corresponding to disaster damage from the same year and include the full first-stage results in the Supporting Information Appendix. For the first-stage and all other regression results using RE Tobit, we report the estimates of unconditional marginal effects using the Delta method for the ease of interpretation.

First, we show that hazard magnitude measures are highly predictive of disaster damage. The rainfall anomaly and the hurricane count variables are all statistically significant with the expected positive sign, indicating a county's damage increase with higher-than-usual precipitation and hurricane intensity. Of note, hurricanes of Categories 3 and above are shown to be particularly destructive; such an event would on average result in an almost fivefold increase in local property damage.

Concerning the socioeconomic and demographic variables, our estimates are mostly consistent across disaster damage lagged by 0–2 years (columns 1–3). We observe that a county's per capita personal income lacks statistical significance, and this is presumably because higher income communities have greater economic exposure to hazards while also having more resources for investing in risk mitigation and resilience. When controlling for income, counties with higher poverty rates or lower median housing values are found to have significantly more damage, suggesting that communities with lower socioeconomic status are less capable of coping with hazards and thus suffer greater losses. The negative correlation between damage and housing values may suggest that higher priced homes are more structurally sound and resilient to shocks than the lower priced ones, or possibly wealthier communities are more likely to implement risk mitigation strategies to protect their assets. Meanwhile, our results show that counties with lower educational attainment and a higher percentage of Black or Hispanic populations, on average, experienced less disaster damage. This pattern may appear somewhat counter-intuitive but also illustrate the complex relationship between social vulnerability and disaster losses likely due to the uneven exposure and loss (under-)reporting and assessment practices.[12] Additionally, we do not find a strong correlation between a county's level of urbanization and its disaster damage, although counties with larger populations (after controlling for land areas) are found to have more per capita damage. Interestingly, we find the Democratic voter variable correlates with disaster damage, while the estimated coefficient is only significant for contemporaneous damage (column 1).

Concerning the geographic risk attributes, we find that flood risk (measured by the ratio of 100-year flood zone) and hurricane exposure are positively associated with damage. After accounting for these variables, coastal counties tend to experience less damage than non-coastal counties, which may suggest better adaptation to flood and storm hazards in the coastal regions.

6.2 | Second-stage results: Modeling disaster aid distribution by program

6.2.1 | Programs with public recipients

Table 5 reports the second-stage results modeling distribution of aid from the four programs targeting state and local governments and other public entities (PA, HMGP, FMA, and PDM). We find that aid distribution is highly driven by more recent damage for disaster programs requiring PDDs (PA and HMGP). Among all these aid programs, PA is the most responsive to disaster damage. Our estimates suggest that a

[12] One possible explanation is that these communities tend to have lower economic and asset exposure (that is not fully captured by the income variables). There could also be a potential reporting bias, as disaster loss information about many disadvantaged groups is not fully collected (Bakkensen & Blair, 2020).

TABLE 4 First-stage results (modeling county-level flood- and storm-related damage).

Variables	(1) Damage (*t*)	(2) Damage (*t*-1)	(3) Damage (*t*-2)
Rainfall anomaly	0.235***	0.244***	0.254***
	(0.00418)	(0.00426)	(0.00443)
# of hurricanes (category 1)	2.106***	2.117***	2.002***
	(0.0889)	(0.0861)	(0.0902)
# of hurricanes (category 2)	2.384***	2.438***	1.865***
	(0.205)	(0.203)	(0.219)
# of hurricanes (category 3+)	4.848***	4.910***	5.079***
	(0.257)	(0.260)	(0.377)
Personal income per capita (log)	−0.127	0.0129	0.0869
	(0.0851)	(0.0852)	(0.0857)
Population (log)	0.139***	0.135***	0.146***
	(0.0173)	(0.0173)	(0.0173)
Poverty rates (%)	0.0104***	0.0111***	0.0162***
	(0.00386)	(0.00387)	(0.00389)
Median housing values (log)	−0.295***	−0.321***	−0.308***
	(0.0609)	(0.0608)	(0.0609)
Lower education (= 1)	−0.0734***	−0.0577**	−0.0700**
	(0.0272)	(0.0273)	(0.0275)
Percentage of African American (%)	−0.00607***	−0.00211	−0.00127
	(0.00181)	(0.00180)	(0.00181)
Percentage of Hispanic (%)	−0.0123***	−0.0119***	−0.0122***
	(0.00171)	(0.00171)	(0.00171)
Percentage of renters (%)	−0.00377	−0.00274	−0.00509**
	(0.00255)	(0.00255)	(0.00255)
Metropolitan (= 1)	−0.0617	−0.0314	−0.0162
	(0.0388)	(0.0389)	(0.0391)
Urban (= 1)	−0.0116	0.0156	0.0385
	(0.0327)	(0.0327)	(0.0329)
Own-source revenues per capita (log)	−0.0143	−0.0245	−0.00110
	(0.0173)	(0.0175)	(0.0176)
Democratic votes (%)	0.00446***	0.000180	−0.00207
	(0.00134)	(0.00134)	(0.00134)
Swing county × election year	0.112	0.0199	0.0575
	(0.0696)	(0.0699)	(0.0709)
County area (log)	0.113***	0.104***	0.0729**
	(0.0320)	(0.0319)	(0.0319)
Ratio of 100-year flood zone (%)	0.00397***	0.00365***	0.00431***
	(0.00128)	(0.00128)	(0.00128)
Hurricane exposure	0.0161***	0.0148***	0.0177***
	(0.00211)	(0.00210)	(0.00211)
Coastal county	−0.0791	−0.0495	−0.0697
	(0.0519)	(0.0517)	(0.0518)
Observations	59,742	59,742	59,742
Number of counties	3000	3000	3000

Note: Each column reports the hazard variables only corresponding to damage from the same year. All specifications include hazard variables in year *t*, *t*-1, and *t*-2 as well as year dummies and state dummies. The full first-stage results are in Also included in the Supporting Information Appendix are results using an alternative Table 2. The time-varying social characteristics variables are lagged by 2 years. Standard errors are reported in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 5 Second-stage results (distribution of disaster grant with public recipients).

Program	PA	HMGP	FMA	PDM
Disaster damage (*t*)	0.312***	0.136***	0.00186*	0.00506**
	(0.00853)	(0.00449)	(0.00101)	(0.00217)
Disaster damage (*t*-1)	0.316***	0.00763*	0.000739	−0.00213
	(0.00845)	(0.00463)	(0.000994)	(0.00232)
Disaster damage (*t*-2)	0.101***	−0.0250***	3.76e-05	−0.00861***
	(0.00847)	(0.00488)	(0.00107)	(0.00246)
Personal income per capita (log)	0.0474	0.00903	−0.000973	−0.000322
	(0.0519)	(0.0242)	(0.00767)	(0.0119)
Population (log)	0.0716***	0.0502***	0.0114***	0.0185***
	(0.0100)	(0.00426)	(0.00153)	(0.00204)
Poverty rates (%)	−0.000120	−0.00350***	−0.000828**	−8.49e-05
	(0.00236)	(0.00111)	(0.000386)	(0.000566)
Median housing values (log)	0.0457	−0.0109	0.00411	0.0141*
	(0.0359)	(0.0154)	(0.00498)	(0.00752)
Lower education (= 1)	−0.0129	−0.0153*	−0.00735***	−0.000126
	(0.0176)	(0.00912)	(0.00270)	(0.00479)
Percentage of African American (%)	−0.00321***	−0.000761*	0.000237	−0.000325
	(0.00102)	(0.000422)	(0.000153)	(0.000235)
Percentage of Hispanic (%)	−0.00277***	−0.000449	0.000130	−0.000281
	(0.000999)	(0.000439)	(0.000138)	(0.000211)
Percentage of renters (%)	−0.00413***	0.00105*	0.000343*	0.000335
	(0.00149)	(0.000618)	(0.000199)	(0.000315)
Metropolitan (= 1)	−0.0185	0.0157	−0.00138	−0.0264***
	(0.0230)	(0.0101)	(0.00262)	(0.00487)
Urban (= 1)	0.00266	0.0127	−0.00293	−0.0173***
	(0.0190)	(0.00818)	(0.00275)	(0.00413)
Own-source revenues per capita (log)	0.0203*	−0.0108**	0.000273	−0.00254
	(0.0106)	(0.00466)	(0.00135)	(0.00212)
Democratic votes (%)	0.00686***	0.00116***	−0.000178	0.000373**
	(0.000811)	(0.000378)	(0.000119)	(0.000185)
Swing county × election year	−0.0716	0.0761***	0.00101	−0.00561
	(0.0482)	(0.0222)	(0.00614)	(0.0117)
County area (log)	−0.0556***	0.0101	−0.00166	0.00586*
	(0.0181)	(0.00727)	(0.00232)	(0.00337)
Ratio of 100-year flood zone (%)	0.000653	0.000282	5.12e-05	−0.000221
	(0.000696)	(0.000276)	(8.97e-05)	(0.000159)
Hurricane exposure	0.00623***	0.000292	0.000931***	0.00101***
	(0.00117)	(0.000455)	(0.000154)	(0.000255)
Coastal county	0.0580**	0.0269**	0.00214	0.00140
	(0.0288)	(0.0112)	(0.00345)	(0.00554)
Observations	59,742	59,742	59,742	59,742
Number of counties	3000	3000	3000	3000

Note: Each column includes year dummies and state dummies in the regression model. The time-varying social characteristics variables are lagged by 2 years. Standard errors are reported in parentheses.

Abbreviations: FMA, Flood Mitigation Assistance; HMGP, Hazard Mitigation Grant Program; PA, Public Assistance; PDM, Pre-disaster Mitigation.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

10% increase in damage is expected to increase PA grants by 3% in the same year and cumulatively by more than 4% over the following 2 years. Compared to PA, HMGP is primarily responsive to the contemporaneous disaster, whose grants increase by 1% with respect to a 10% increase in damage. But this response becomes negative for earlier disasters (in year *t*-2), which is possibly because counties acquiring more mitigation funding due to the contemporaneous shock may have lower needs for such aid in later years. For FMA and PDM (the other two pre-disaster mitigation programs with no PDD requirements and comprising a much smaller fraction of the disaster aid enterprise), we find that their aid is also positively influenced by the contemporaneous damage, suggesting that counties that just experienced disasters are also more likely to apply for mitigation grants in addition to federal relief funds. But it should be noted that the estimated disaster effect (in year *t*) is much smaller in magnitude than the estimates for PA and HMGP. Similar to HMGP, the disaster effect turns negative for PDM aid 2 years later.

Concerning the social factors, we show that consistently for all these programs, counties with large populations receive significantly more federal aid per capita. Our results show that personal income is statistically insignificant for explaining aid distribution, but after controlling for income, counties with higher poverty rates and lower educational attainment receive less aid from HMGP and FMA. This suggests that the federal hazard mitigation grants may underserve socially and economically disadvantaged communities. For these two programs, we also show that their grant funds are positively correlated with the ratio of renters, although the coefficients are only marginally significant with a small magnitude. We find that significantly fewer PA grants are received by counties with larger Black or Hispanic populations, or more renters, suggesting that this major FEMA program underserves minority groups. Results also show that more PDM grants are distributed to counties with higher median housing values or rural counties (the omitted category). This finding is actually expected because PDM allows a maximum 90% federal cost-share for small, impoverished communities. Overall, our findings indicate that when controlling for sustained damage, more disaster aid targeting public entities goes to counties with better socioeconomic conditions, suggesting that these programs may underserve the vulnerable communities and exhibit lower social equity performance.

As for local fiscal capacity, we find that county government own-source revenue is positive and significant for PA grants. This is consistent with our expectation because receiving PA grants requires a local share of eligible project costs, which may potentially favor counties with more fiscal resources. Surprisingly, own-source revenue is found to negatively correlate with the amount of HMGP grants, although HMGP also requires local contribution. Nonetheless, it should be noted that significantly more counties apply for and receive funds from PA than those receiving HMGP grants, which usually take a longer time to process, and it is possible that counties receiving more PA funds are less likely to apply for HMGP grants. Regarding political ideology, we find that counties with more Democratic voters receive significantly more disaster aid from PA, HMGP, and PDM. Yet, we do not find strong evidence of political motivation driving disaster aid allocation from the federal distributor's perspective. The interaction term between swing county and election years is only statistically significant and positive for HMGP.

In terms of geographic and risk attributes, we find that counties with higher hurricane exposure generally receive more public disaster aid for post-disaster recovery and pre-disaster mitigation (PA, FMA, and PDM). Also, more post-PDD aid (PA and HMPG) is provided to coastal counties, after controlling for disaster damage.

6.2.2 | Programs with private recipients

Table 6 reports our second-stage results for IHP and DLA, two programs targeting private agents. Notably, the datasets (from FEMA and SBA) for both programs distinguish different recipient types (homeowners and renters for IHP and homeowners and business owners for DLA). Thus, we estimate separate regressions for recipient-specific grants or loans (in columns 2, 3, 5, and 6) and report the results for the total program funds in columns 1 and 4. Since both programs offer assistance contingent on PDDs, we find that their outlays are highly driven by contemporaneous disaster damage. Our estimates indicate that 1% increase in flood- and storm-related damage would lead to a 0.2% increase in both the total IHP aid and total DLA loans. Additionally, the 1-year lagged damage also have a statistically significant and positive effect on DLA loans, although the magnitude of the effect is much smaller than that of the contemporaneous damage. For both programs, we show that the amount of assistance decreases with the disaster damage incurred 2 years ago.

Regarding the social factors, we show that population size consistently exhibits a significant, positive correlation with the private receipt of disaster assistance, which is similar to our previous findings for programs with public recipients. Counties with higher personal income receive significantly less IHP aid and DLA loans for homeowners. In the meantime, we find that counties with higher median housing values receive significantly more disaster assistance from both IHP and DLA programs. Also noteworthy is that more IHP and DLA assistance (particularly those directed toward homeowners) is received by counties with lower proportions of renters. One possible explanation is that the relief aid is used to cover some of private asset loss, so the aid positively correlates with housing values and better serves homeowners rather than renters. But more lower income people or poorer communities might be eligible for such post-disaster assistance. It is somewhat surprising to observe a negative correlation between IHP aid for renters and a county's percentage of renters. However, the estimated coefficient is small, suggesting relatively small economic significance.

TABLE 6 Second-stage results (distribution of disaster assistance with private recipients).

Program	IHP total	IHP homeowners	IHP renters	DLA total	DLA homeowners	DLA business
Disaster damage (*t*)	0.191***	0.182***	0.0919***	0.210***	0.184***	0.111***
	(0.00441)	(0.00423)	(0.00212)	(0.00542)	(0.00480)	(0.00340)
Disaster damage (*t*-1)	−0.000968	−0.000762	−0.00282	0.0543***	0.0398***	0.0355***
	(0.00470)	(0.00449)	(0.00222)	(0.00535)	(0.00466)	(0.00337)
Disaster damage (*t*-2)	−0.0287***	−0.0263***	−0.0133***	−0.0137**	−0.0154***	−0.00778**
	(0.00511)	(0.00489)	(0.00243)	(0.00570)	(0.00506)	(0.00369)
Personal income per capita (log)	−0.0841***	−0.0790***	−0.0444***	−0.0551*	−0.0949***	−0.000642
	(0.0249)	(0.0238)	(0.0121)	(0.0298)	(0.0268)	(0.0193)
Population (log)	0.0543***	0.0517***	0.0294***	0.105***	0.0917***	0.0548***
	(0.00426)	(0.00409)	(0.00208)	(0.00491)	(0.00454)	(0.00309)
Poverty rates (%)	0.000667	0.000904	0.000504	0.00475***	0.00216*	0.00251***
	(0.00104)	(0.000994)	(0.000503)	(0.00130)	(0.00115)	(0.000860)
Median housing values (log)	0.0440***	0.0425***	0.0260***	0.0858***	0.0443***	0.0705***
	(0.0154)	(0.0147)	(0.00757)	(0.0181)	(0.0164)	(0.0117)
Lower education (= 1)	0.0151*	0.0152*	0.0101**	−0.0114	−0.000607	−0.0139**
	(0.00873)	(0.00835)	(0.00420)	(0.0105)	(0.00930)	(0.00685)
Percentage of Black (%)	0.00160***	0.00147***	0.00112***	4.69e-05	−0.000120	0.000407
	(0.000375)	(0.000359)	(0.000180)	(0.000465)	(0.000412)	(0.000298)
Percentage of Hispanic (%)	0.000185	0.000144	0.000212	−0.000287	−0.000516	0.000111
	(0.000411)	(0.000394)	(0.000196)	(0.000472)	(0.000423)	(0.000300)
Percentage of renters (%)	−0.00185***	−0.00198***	−0.000681**	−0.00186***	−0.00272***	0.000323
	(0.000592)	(0.000567)	(0.000284)	(0.000707)	(0.000640)	(0.000444)
Metropolitan (= 1)	0.00581	0.00573	0.00616	0.0266**	0.0201**	0.0156**
	(0.00949)	(0.00908)	(0.00453)	(0.0113)	(0.0100)	(0.00710)
Urban (= 1)	0.0274***	0.0269***	0.0148***	0.0364***	0.0370***	0.0204***
	(0.00771)	(0.00737)	(0.00380)	(0.00948)	(0.00846)	(0.00623)
Own-source revenues per capita (log)	−0.00898*	−0.00798*	−0.00448**	0.000857	−0.00463	−0.00154
	(0.00464)	(0.00444)	(0.00224)	(0.00574)	(0.00502)	(0.00366)
Democratic votes (%)	0.000125	9.38e-05	−8.65e-05	0.000753*	0.00166***	8.72e-05
	(0.000370)	(0.000354)	(0.000180)	(0.000432)	(0.000387)	(0.000281)
Swing county × election year	0.0580**	0.0542**	0.0214*	0.00113	0.00776	0.00495
	(0.0232)	(0.0222)	(0.0110)	(0.0300)	(0.0256)	(0.0195)
County area (log)	−0.0487***	−0.0481***	−0.0221***	−0.0349***	−0.0387***	−0.00684
	(0.00763)	(0.00731)	(0.00369)	(0.00848)	(0.00778)	(0.00531)
Ratio of 100-year flood zone (%)	0.000545**	0.000520**	0.000255**	0.000447	0.000141	0.000556***
	(0.000223)	(0.000214)	(0.000105)	(0.000291)	(0.000257)	(0.000179)
Hurricane exposure	0.000547	0.000504	0.000737***	0.00224***	0.00189***	0.00128***
	(0.000395)	(0.000379)	(0.000183)	(0.000492)	(0.000436)	(0.000303)
Coastal county	0.0557***	0.0523***	0.0288***	0.0378***	0.0341***	0.0252***
	(0.0103)	(0.00983)	(0.00485)	(0.0123)	(0.0110)	(0.00763)
Observations	53,744	53,744	53,744	59,742	59,742	59,742
Number of counties	2999	2999	2999	3000	3000	3000

Abbreviations: DLA, Disaster Loan Assistance; IHP, Individuals and Households Program.

Our results for IHP show that more of its aid is allocated to counties with lower educational attainment, a higher percentage of Black populations, or fewer fiscal resources, suggesting the program's relatively better social equity performance. We find that more DLA loans for businesses are distributed to counties with relatively higher poverty rates but also higher educational attainment, demonstrating mixed evidence on the program's distributional patterns in relation to social vulnerability. For both programs, we find that they tend to favor urban counties or metropolitan counties (only significant for DLA) rather than rural communities, after controlling for other socioeconomic conditions. Regarding political factors, the Democratic voter variable is found to be largely insignificant for private receipt of disaster assistance, except in the case of DLA loans for homeowners. We also show that significantly more IHP aid is distributed to swing counties during election years.

Regarding the geographic patterns, we find that coastal counties on average receive significantly more assistance from both IHP and DLA. Additionally, more IHP aid is provided to counties with higher flooding risks measured by its ratio of 100-year flood zones, and more DLA loans are received by counties with higher hurricane exposure.

6.3 | Discussion and additional tests

To discuss our key findings, first, we show that the distribution of federal disaster grants, particularly from the PDD-required programs, is heavily driven by the more recent disaster damage. For the four programs that require a PDD considered in this study, we estimate that a 10% increase in damage is associated with a 3% increase in PA aid, a 1.4% increase in HMGP grants, and a 2% in IHP and DLA assistance each in the same year. To put these figures in perspective, every 10 dollars in disaster damage is associated with about one-dollar federal outlays through the four programs (based on the sample mean of both damage and grants by program) incurred in the same year. Among all these aid programs, FEMA's largest program PA is the most responsive to damage in terms of both magnitude and time length. While our finding that more damage leads to more aid is consistent with existing disaster aid research (e.g., Domingue & Emrich, 2019; Emrich et al., 2020) and the international aid literature (Becerra et al., 2014; Yang, 2008), we show that the disaster damage's effect on aid outlays of all these programs would be underestimated if we did not instrument for damage.[13] This underlines the importance of addressing the endogeneity of disaster damage, particularly when damage is often used to gauge the need for and size of government disaster-related spending.

Also importantly, our first-stage results indicate the uneven distribution of county-level damage from floods and storms and their correlation with local socioeconomic conditions and geographic risk attributes. While the disaster vulnerability literature generally suggests that vulnerable populations are more adversely affected by natural hazards (Cutter et al., 2003), our results show that the vulnerability-related socioeconomic and demographic characteristics may either positively or negatively correlate with disaster damage. In particular, we find that counties with higher housing values or lower poverty rates experience less damage (presumably because of more resilience investment in these communities), and this suggests that even when more damage triggers more federal aid, richer communities do not obtain more grants than their poorer counterparts because of more damage incurred. Meanwhile, we also find that disaster damage is lower in counties with more Black or Hispanic populations. These mixed findings can be attributed to a combination of factors including lack of resources and capacity for mitigation, lower economic exposure, and limited damage assessment and reporting practices as found in previous research (Emrich et al., 2022; Raker, 2023; Bakkensen and Blair, 2020). They also may reflect the complex societal mechanisms influencing disaster-induced economic damage (V. K. Smith et al., 2022), which necessitates more investigations of the damage–vulnerability relationship.

In addition to disaster damage, our second-stage results further elucidate how a county's receipt of disaster aid correlates with its socioeconomic and demographic characteristics, local government resource, political leaning, and geographic risks. All these factors may influence a locality's inclination and capacity to acquire federal grants when they experience similar level of disaster damage, thereby entailing important equity implications. Notably, we find that for all the disaster programs we evaluated, federal aid is disproportionately allocated to counties with larger populations. This is likely because disasters that occur in more populous counties are more salient and thus attract more attention and federal resources. Larger counties may also have larger government and administration systems and greater public resources, providing them with a comparative advantage in applying for federal grants. This finding, meanwhile, suggests that federal disaster aid may underserve people living in less populated counties.

As an important economic indicator, personal income is found to be insignificant for predicting aid outlays from disaster programs targeting public entities but negatively correlate with outlays from programs with private recipients.[14] To more explicitly examine income-based disparity in disaster aid distribution, we estimate a parsimonious model with only income and population as the social factor. We find that counties with higher incomes receive significantly more aid from most public disaster programs (PA, HMGP, and FMA), while lower-income counties receive more assistance from IHP and

[13] In the Supporting Information Appendix Table 2, we report the Tobit RE model results without using IVs for disaster damage. For instance, the estimated coefficient of disaster damage (in year t) for PA grants is 0.18, much smaller than the estimate of 0.31 in our IV model results.

[14] We note that our finding of the income effect on IHP grants generally resonates with the results in Emich et al. (2020) and Emrich et al. (2022).

DLA, aligning with our baseline finding.[15] Regarding political factors, we show that the percentage of Democratic voters positively correlates with the outlays from aid programs targeting public entities (PA, HMGP, and PDM) but is less significant for aid programs targeting private entities. This finding seems to resonate with the prior literature suggesting that Democrats tend to perceive greater disaster risks, assign more responsibility to the government for managing disasters, and expect more federal disaster aid than Republicans (Botzen et al., 2016; Wehde & Nowlin, 2021). Such inclinations may make counties with a higher proportion of Democratic voters more likely to apply for federal grants for public projects such as restoration of public infrastructure or mitigation facilities.

Furthermore, our results on the geographic risk variables shed light on another dimension of equity by elucidating whether more federal aid is distributed to more risky communities. Our results on the three hazard mitigation programs (HMGP, FMA, and PDM) indicate that more such federal grants are allocated to counties at higher risk of flooding or storms (especially after accounting for their sustained damage), thereby helping address the standing inequalities in geographic risks. This pattern appears to be similar to the findings in Tyler et al. (2023). While PA focuses primarily on disaster recovery, some of its projects such as the restoration of public infrastructure can also have risk mitigation functions. When viewed in this context, more PA funds distributed to higher risk regions may also suggest good equity performance. Similarly, we observe more aid from programs targeting private recipients also flows to coastal counties at higher risk of flooding or storm hazards. The question of whether such geographic distribution is socially equitable hinges on the characteristics of residents living in the higher risks regions. If more socially vulnerable populations live in these hazard-prone regions, they might receive additional federal assistance to offset disaster losses, as suggested by our estimates. Nonetheless, it is important to acknowledge the heterogenous location preferences across subgroups of populations conditional on socioeconomic status and risk tolerance (e.g., wealthy people may prefer to live on the coast as they value the coastal amenity despite high flooding risks).

In addition to these main results, we perform additional robustness checks which are all reported in the Supporting Information Appendix. Because a record high number of counties received PDDs during Hurricane Katrina in 2005, we re-estimated our models by excluding the year 2005 and found consistent results. In another robustness check, we included the count of other PDDs (for tornados, earthquakes, winter storms, and wildfires) received by a county-year as a control variable in our regressions. All these results are highly consistent with our main findings. Also included in the Supporting Information Appendix are results using an alternative Poisson model for the second stage and estimates from the reduced form model to understand the aggregate effect of social factors and other locality characteristics on disaster aid outlays.[16]

7 | CONCLUSION

As increased extreme weather events threaten communities and challenge local government operations and finances, it is imperative to examine the role of federal disaster programs in assisting communities in preparing for, mitigating, responding to, and recovering from natural hazards. This study presents the first nationwide analysis of major federal disaster grant programs with a particular focus on their social equity performance tied to program designs. By compiling a rich panel dataset combining county-level disaster aid, damage, and socioeconomic, demographic, local government, and geographic risk attributes, we find varying degrees of social disparities in federal disaster aid distribution by program. As hypothesized, results indicate that programs for government recipients targeting community recovery or mitigation tend to favor counties with better socioeconomic conditions. Specifically, we show that more PA grants are received by counties with fewer Black residents or renters and with more own-source revenues; more mitigation aid (HMGP, FMA, and PDM) is received by counties with lower poverty rates, higher educational attainment, or higher housing values. All these programs have cost-share requirements, and their relatively unequal distributional pattern is consistent with our first hypothesis that the cost-share requirement can direct more aid to less vulnerable localities due to the resource burden. Moreover, the mitigation grant programs all have yearly funding limits, and particularly FMA and PDM involve more competitive application procedures. Their distributional patterns further support our hypothesis that these program designs (funding cap, competitive application, and technical analysis requirement) impose higher administrative burdens and thus deliver less aid to disadvantaged, lower-capacity localities.

On the other hand, we find programs targeting individual relief and recovery to be more equitable in their aid distribution. Specifically, results show that more IHP aid is provided to counties with lower personal incomes, more Black populations, lower educational attainment, or fewer fiscal sources. More DLA loans are distributed to counties with lower incomes and higher poverty rates. As discussed earlier, this is likely because the aid programs targeting private recipients have relatively more simplified application procedures and no cost-share requirements or program-level

[15] We performed this test considering that income correlates with many other socioeconomic and demographic variables included in our main model. We report our results in the Supporting Information Appendix Table 4.

[16] We estimate a reduced form model (using RE Tobit regression) in which the endogenous damage variables are replaced by our instrumental variables (distributed lag of hazard magnitude variables), with results reported in the Supporting Information Appendix Table 8. This approach estimates the aggregate effect of local community characteristics on disaster aid outlays but does not disentangle their direct effects on access to aid (second stage) and indirect effects through disaster damage (first stage). Compared to the reduced form model, we believe that our main two-stage model aligns better with our conceptual framework.

funding limit, which allows assistance to be provided as long as one meets the eligibility requirement.

Our study provides important implications for the ongoing discussion about the federal disaster policy and assistance programs, as we show major disaster programs for state and local governments provide disproportionately less benefit to counties with lower socioeconomic status. Such aid-need mismatch can be potentially remedied by modifying the program design, for example, lowering the cost-share requirement for less affluent communities. To address the administrative burden faced by localities, FEMA and other federal agencies should also provide more procedure guidance and technical support to assist local and state governments in the process of applying for disaster grants. Moreover, more hazard mitigation grants should be made accessible to local governments and communities, particularly those with more vulnerable populations residing in risky places.

Lastly, it is important to acknowledge the limitations of this research. While we have included a wide range of social factors to model the distributional pattern of federal disaster programs, there may be other unobserved confounding factors or cross-county heterogeneity that could affect aid allocation that are not accounted for in our model. Thus, we caution that our estimates of social factors should be interpreted as correlation rather than causation. Moreover, we also acknowledge that counties are a relatively large geographic unit comprising heterogeneous communities and neighborhoods. The county-level attributes may not precisely capture the characteristics of disaster aid recipients and could introduce noise to the interpretation of our estimates. Therefore, it would be crucial for future research to examine disaster aid distribution at a finer geographic resolution or using micro-level data on disaster aid payments to recipients (with their socio-demographical information). Our study can be extended in several other directions. For instance, our research design can be applied to evaluate more disaster programs such as HUD's Community Development Block Grant Disaster Recovery Program, or to examine other types of natural hazards, such as wildfire or tornados. Furthermore, recent studies have examined the effectiveness and welfare implications of federal disaster aid (Davlasheridze & Miao, 2021; Davlasheridze et al., 2017) and suggest that disaster preparedness and mitigation grants are more effective for reducing future disaster damage than the relief and recovery aid. Our findings on aid allocation patterns can be potentially integrated with research on the societal effects of disaster aid to further elucidate the social disparity in post-disaster recovery trajectories and community resilience.

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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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