Check for updates

Article

American Review of Public Administration
1–17
© The Author(s) 2019
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/0275074019856122
journals.sagepub.com/home/arp
SAGE

Social Vulnerability and Procedural Equity: Exploring the Distribution of Disaster Aid Across Counties in the United States

Simone J. Domingue[1] and Christopher T. Emrich[2]

Abstract
To date, there has been limited research conducted on disaster aid allocation across multiple regions and disasters within the United States. In addition, there is a paucity of research specifically connecting social indicators of vulnerability to public assistance grants aimed at restoring, rebuilding, and mitigating against future damages in disasters. Given these gaps, this article inquires as to whether the Federal Emergency Management Agency's (FEMA's) public assistance program is characterized by procedural inequities, or disparate outcomes for counties with more socially vulnerable populations. Specifically, this article analyzes county-level FEMA's Public Assistance distribution following major disaster declarations, while controlling for damages sustained, population, household counts, and FEMA Region. Results indicate that FEMA's Public Assistance program operates well when accounting only for disaster losses across the years, however, findings also show that county social conditions influence funding receipt. Although socioeconomic characteristics were significant drivers of assistance spending, additional vulnerability indicators related to county demographic and built environment characteristics were also important drivers of receipt. Cases of both procedural inequity and equity are highlighted, and implications for equitable disaster recovery are discussed along with recommendations.

Keywords
social vulnerability, inequality, disaster impact, public assistance grants

Problem Identification and Introduction

Governments provide significant aid and assistance to individuals and communities following major disasters, much in the form of public assistance (PA) funds for infrastructure repairs and mitigation. 2017's hurricanes and wildfires are just the latest example of disasters affecting the United States, resulting in calls for upward of $80 billion in government assistance (Zanona & Marcos, 2017). The deadly conditions created by crippled infrastructure systems in Puerto Rico following Hurricane Maria (and the ensuing struggle for government aid) clearly underscore the importance of public aid and administrative equity for the well-being of individuals. Since the passage of the 1988 Stafford Act, federal disaster assistance has been the primary source of recovery aid for individuals and communities across the nation damaged by major disasters such as hurricanes, wildfires, tornadoes, and other severe events.

Local and state governments also rely heavily on federal funds distributed by the Federal Emergency Management Agency (FEMA). Despite the importance of federal disaster aid in this context, there are a number of research gaps regarding how federal disaster aid is distributed, especially as it relates to the unequal patterns of exposure, susceptibility to harm, and recovery from disasters that coincide with social, political, and economic characteristics of people and places (for reviews, see Cutter, Boruff, & Shirley, 2003; Finch, Emrich, & Cutter, 2010; Fothergill, Maestas, & Darlington, 1999; Norris, Friedman, Watson, & Byrne, 2002; Tierney, 2006; Wisner, Blaikie, Cannon, & Davis, 2004). A long history of disaster research has identified those characteristics associated with disparate exposures and impacts—including race, socioeconomic status, age, disability, and language proficiency (Cutter & Emrich, 2006; Fothergill & Peek, 2004; Morrow, 1999; Thomas, Phillips, Lovekamp, & Fothergill, 2013; Reid 2013), and social vulnerability indices (such as that developed by Cutter, Boruff, and Shirley, 2003) have been developed to capture the wide range of socioeconomic, demographic, and built environment conditions that are associated with disaster inequalities. Few studies, however,

[1]University of Colorado, Boulder, USA
[2]University of Central Florida, Orlando, USA

Corresponding Author:
Simone J. Domingue, Department of Sociology and Natural Hazard Center, University of Colorado, UCB 327, Ketchum 195, Boulder, CO 80309, USA.
Email: simone.domingue@colorado.edu

have assessed administrative disaster aid distribution processes from this comprehensive social vulnerability perspective. Aid distribution systems stymie equitable disaster recovery if vulnerable areas with vulnerable populations receive less funding than counterparts with similar levels of damages. As such, a current need for empirical assessment of disaster aid distribution through what public administration and environmental justice scholars call a "social equity lens" exists (Bowen & Wells, 2002). This process, emphasizing how administrative processes can be grounded to yield more fair distributions, will support public administration's main goal of improving equality, justice, security, efficiency, and effectiveness of public services (Durant & Rosenbloom, 2017; Guy & McCandless, 2012).

A concurrent dearth in the literature focusing specifically on public benefit disaster aid indicates a need for more directed and concrete assessments across this domain. PA aid restores public infrastructure, such as public hospitals, critical care facilities, and utility and transportation infrastructure. PA funds granted after disasters provide immediate threat response support, funds for recovery from sustained damages, and funding for disaster mitigation at specific impact locations. Studies to date have not analyzed PA funding distribution over multiple regions, disasters, time frames, or in association with underlying social characteristics to determine procedural equity in funding allocation.

These research gaps form the basis of this inquiry into in how PA disaster aid is distributed in the United States. This article draws from scholarship on procedural equity and analyzes interactions between county-level socioeconomic characteristics and FEMA's county-level PA fund distribution following major disasters in the years 2012-2015. We view procedural equity as just distributive processes and outcomes (Gooden, 2015), defining an *inequity* as a case when highly socially vulnerable counties receive a lesser benefit from federal disaster relief than other counties experiencing similar disaster impacts. Socially vulnerable counties are more dependent upon federal assistance, have less resources for recovery, and have highly impacted populations (Krueger, Jennings, & Kendra, 2009). As such, this research aims to prevent disparities in recovery happening through the process of PA distribution by using pre-event social determinants of vulnerability. By connecting social indicators of vulnerability to PA funds, this analysis identifies both best practices and areas where programmatic or policy changes can facilitate more effective and equitable disaster recovery spending.

Procedural Equity and Government Programs

Preeminent environmental justice scholar, Robert Bullard, defined procedural equity as the degree to which fair treatment characterizes policies and programs (Bullard, 2005). Procedural inequities, and the ensuing disparate distribution of resources and capabilities they produce, disproportionally affect racial and ethnic minorities and lower income and working-class communities (Bullard, 2008; Cole & Foster, 2001; Harrison, 2014; Mohai, Pellow, & Timmons, 2009; Muller, Sampson, & Winter, 2018; Pellow, 2017; Schlosberg, 1999, 2009; Shrader-Frechette, 2002). Although scholars recognize that outward bias and discriminatory intent are still extant features of society, they also stress that procedural inequity is part of the commonplace proceedings of bureaucratic organizations and thus see systems of governance as being characterized by institutionalized processes that privilege certain members of society (Morello-Frosch, 2002; Pellow, 2000; Pulido, 2015).

Procedural inequities in local and national government programs may produce or reproduce disparate distributions of environmental burdens across communities. For instance, although minority communities more often reside in areas burdened with harms, such as toxic waste sites, research shows that policies and programs intended to reduce these burdens do not significantly reduce risk or enhance the capabilities of communities (Bryant & Mohai, 1992; Daley & Layton, 2004; Harrison, 2016; Holifield, 2004; Pearsall & Pierce, 2017; Petrie, 2006). Programs intended to benefit individuals within overburdened communities are not implemented in a manner that is consistent with federal policy, such as the Executive Order on Environmental Justice (Murphy-Greene & Leip, 2002). Remediation programs, such as the U.S. Superfund program, have been proven suboptimal in minority communities and have shown bias in prioritization and program delivery (Burda & Harding, 2014; Lavelle & Coyle, 1992; O'Neil, 2007). Environmental justice scholars have documented how language constitutes a significant procedural barrier, as for example, many Latino communities struggle to access Spanish-translated government documents (Cole & Foster, 2001; Harrison, 2011; Schlosberg, 2009). Importantly, federal agencies are beginning to address these calls for procedural equity. One such example shows the Environmental Protection Agency (EPA) now providing technical assistance grants to communities dealing with complex administrative processes (https://www.epa.gov/environmentaljustice).

Environmental justice literature traditionally focuses on place-based inequalities relating to environmental toxins and pollution, but recently, more research specifically aimed at equity in the disaster context has taken root. For example, in their recent research, Robert Bullard and Beverly Wright (2012) present case studies of inept and unequal government response in the wake of hurricanes, floods, and public health emergencies. Focusing on the U.S. South, Bullard and Wright illustrate how government actions—including emergency response, relief and compensation spending, and rebuilding decisions—often show signs of institutionalized discrimination against people and communities of color. Indeed, in the wake of Hurricane Katrina, researchers documented disparities along racial lines in the way emergency aid, individual assistance, small business loans, and debris removal funds were allocated (Craemer, 2010; Gotham & Campanella, 2011; Hooks & Miller, 2006). Furthermore, a recent legal article (Verchick, 2012) calls for more critical attention to connections between social factors and procedural inequity in the form of disaster aid and compensation in the United States. Verchick also promulgated the idea of codifying procedural equity into law by advocating for an Executive Order on "Disaster Justice" that would be modeled after the current Executive Order on Environmental Justice, resulting in a federal mechanism ensuring the most socially vulnerable groups are given fair compensation following disasters.

Community and County Characteristics Related to Disaster Aid

Hazards and disasters scholars have often focused on social characteristics and the distribution of individual forms of assistance, for example, identifying those characteristics rendering some individuals more successful in navigating bureaucratic channels to receive compensation for losses in disasters; these factors include language, social connectedness, financial resources, and familiarity and trust with local governance (Fotovvat, 2013; Ganapati, 2012; Rivera, 2017; Tierney, Lindell, & Perry, 2001). Such research continues to find that certain groups are excluded from formal aid programs. For example, after the 1989 Loma Prieta earthquake, Bolin and Stanford (2006) found that many low-income Latino Americans and Latino immigrants were not eligible for FEMA assistance because of their multifamily living arrangements. A recent study on disaster aid and justice in the United States found that members of the Latino community and elders were less likely to receive full compensation through federal funding streams following severe flooding in Iowa (Muñoz & Tate 2016). In addition, individual forms of aid distributed post disaster generally privilege property owners and neglect people in urban areas, renters, or people occupying public housing (Peacock, Van Zandt, Zang, & Highfield, 2014; Reid, 2010; Zhang & Peacock, 2009).

Even in light of this powerful empirical evidence of procedural inequality, none of these studies focus on large-scale accumulation of disaster aid specifically intended for public infrastructure. Applying for this aid is the responsibility of institutional actors within the public and civic sectors (i.e., city, county, tribal, state government entities) and not individual home or business owners. Relationships between community members and institutional actors, and between actors at various scales of governance, are important components of securing aid for infrastructure because capacity, coordination, and communication are all needed to successfully traverse complex governance systems (Comfort, Birkland, Cigler, & Nance, 2010; Johnston, Goerdel, Lavich Jr, & Pierce, 2015; Nowell, Steelman, Velez, & Yang, 2018; Rubin, 2009; Smith, 2012). These abilities are requisite in assessing and documenting damages from disasters and accurately completing applications for federal aid. According to FEMA (2017), the federal and state governments are responsible for making county-level officials aware of their eligibility through informational meetings. Moreover, eligible entities can only apply for federal government funding through state officials. Most importantly, the federal government's obligation includes assisting eligible entities within counties in the process of applying for PA projects and determining funding awards (FEMA, 2017).

Areas with fewer resources and more limited capabilities for securing aid may also be the most in need of federal funding. For instance, a Hurricane Andrew recovery study found that resources favored White affluent communities, whereas the poorer Black communities in Florida City lacked the necessary administrative capacities for securing aid (Peacock, Gladwin, & Morrow, 2012). A recent flood recovery study (Rumbach, Makarewicz, & Németh, 2016) also found a positive correlation between strength of local government, affluence, and diverse sources of aid. Local governments that have stronger tax bases may translate revenue into increased time and capacity to seek out funding. Given policy trends toward devolution of emergency management responsibilities to local levels (Gotham, 2012; Krueger et al., 2009; Martin, Levey, & Cawley, 2012; Tierney et al., 2001; Tomes, 2011), government organizations in poorer communities may be increasingly disadvantaged when vying for federal funding. For instance, Klinenberg (2002) expounded on this dynamic in his 1993 Chicago heat wave research, noting how government capacity for serving low-income elderly residents was drastically reduced by neoliberal policy reforms. In addition, Krueger et al. (2009) in a study of county administrative capacity suggest that counties with more urban residents in poverty and have a lower ability to self-fund emergency management operations.

As demonstrated by disaster research, some community and county characteristics are associated with decreased likelihoods of benefiting from disaster aid. However, little comprehensive and systematic evidence exists about these differences, and furthermore, little attention has been paid specifically to PA funding making up one the largest portions of federal spending on disasters in the United States (Platt, 1999). Because vulnerable populations are likely to live in physically exposed areas receiving high levels of damage (Elliot & Pais, 2010, Morrow, 1999; Peacock et al., 2014; Reid 2013), disparities in these allocations may be a mechanism further exacerbating the vulnerability of particular people and places.

To address these knowledge gaps regarding disaster aid distribution, we pose the following research questions:

Research Question 1: Are social indicators of vulnerability associated with lower amounts of PA spending in counties with similar levels of damage?

Research Question 2: What are the most influential social vulnerability indicators?

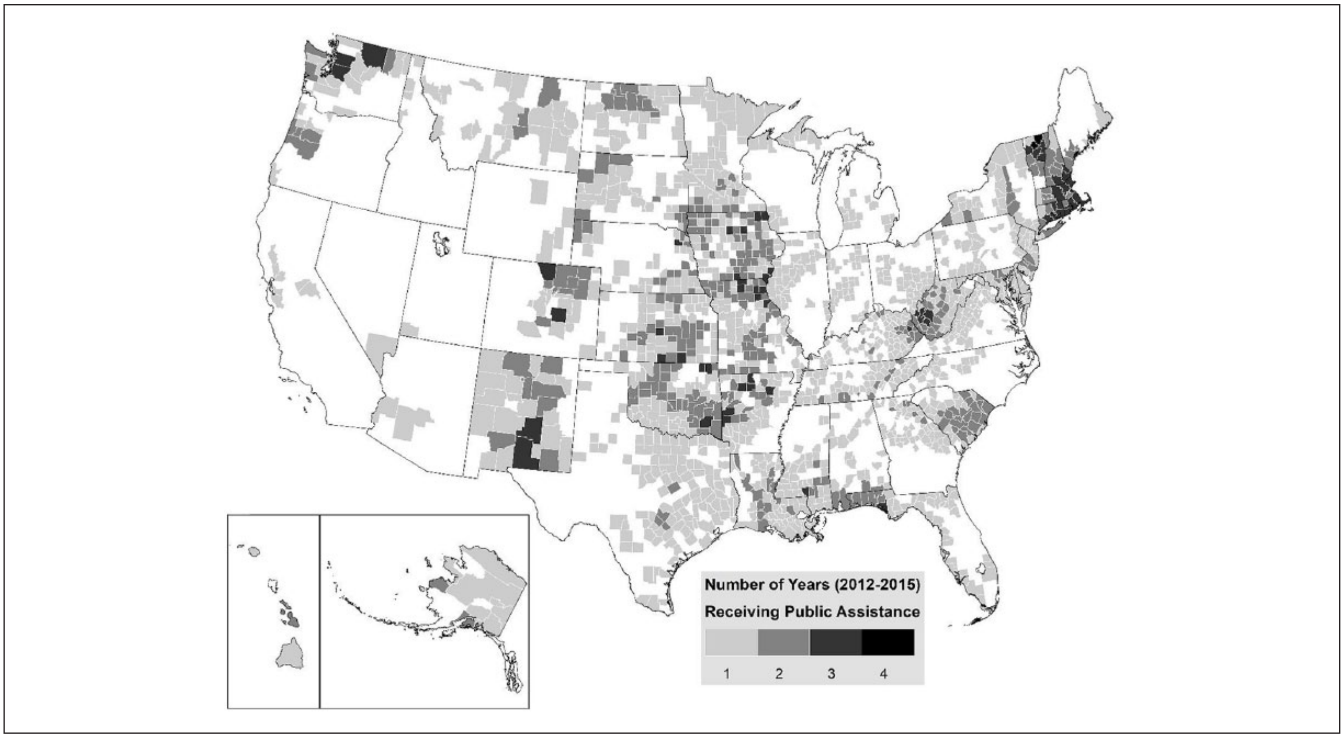

Figure 1. United States county study area.

We use the most recently available and temporally complete data on social vulnerability indicators, damages, and PA spending to analyze the years 2012-2015. We model the distribution of PA spending in counties with similar levels of damage, and control for population density, household counts, and FEMA region to reduce chances of bias in model results. Based on extant literature of disaster aid distribution, we offer the following hypotheses:

> **Hypothesis 1:** There will be inequities in funding distribution across study years, meaning counties with more socially vulnerable populations will be less likely than counterparts to receive PA dollars given similar amounts of damages.
>
> **Hypothesis 2:** The most influential social vulnerability indicators will be socioeconomic and demographic in nature and will be relatively consistent over time.

Data and Method

Study Area

This analysis includes 1,621 U.S. counties receiving FEMA's PA funds between the years 2012 and 2015. PA funds are only made available to presidentially declared disaster areas, a process kicked off by exceeding specific per capita loss thresholds on a county-by-county basis (FEMA, 2017). These counties, 52% of all U.S. counties, are distributed across the United States with a high number of impacted counties in nearly every region of the country, with the exception of the Southwest. Counties in the Great Plains and Midwest, and Mississippi River basin as well as the Gulf and North Atlantic Coasts, and Appalachia have the highest incidence of disasters warranting PA funding (Figure 1). Of these counties, 1,210 had only one presidentially declared PA disaster, 343 saw damages from two disasters, another 65 were impacted by three PA disaster declarations, and only two saw impacts from four PA disasters. These counties are statistically representative of the entire U.S. population in each study year and across the entire time period with no lower than a 99% ± 5.73 confidence interval.

FEMA's PA Data

FEMA's PA program provides federal aid for emergency and long-term repairs for infrastructure (roads, bridges, schools, parks, utilities) maintained by tax dollars. PA funds, one of the largest categories of disaster assistance, are provided to specific entities (state/local governments, tribes, and nonprofit organizations) on an initial 75%–25% cost-share basis. Importantly, PA is not tied to means, and as such, any state, county, and local municipality can attain PA funds if the requisite cost-share is identified (Platt, 1999). PA funds the following types of projects: debris removal, repair of damaged infrastructure, replacement of damaged infrastructure, mitigation, and emergency protective measures. Data on the amount of federal spending for disasters comes from publicly available data released by FEMA through the

OpenFEMA data release program denoting obligated PA project spending following federally declared disasters (https://www.fema.gov/data-feeds).

Due to limitations on specific annual social economic data, disaster losses, and PA spending requiring years for complete accounting, this analysis concentrated on the most recently available data for this study—the federally obligated share of PA spending granted to counties during the years 2012-2015. The unit of analysis is counties because PA data are only geo-referenced at the county level. PA projects were counted and summed to calculate total funding per county for each year. The analysis used funds directed toward individual counties, excluding funds distributed to state governments and those that were deobligated to project recipients. The analysis also excluded United States territories because data for these areas was unavailable at the county level. All values were adjusted for inflation to the year 2016.

First, a per capita federal spending variable was calculated using the total population of counties. Because the per capita PA funding distribution is highly positively skewed, it was transformed by logging it to the base 10 and then subsequently recoded into a three-category variable based on its standard deviation (*SD*) where less than –.5 SD = low, –.5 to .5 SD = medium, and greater than .5 SD = high.

Social Vulnerability Variables

Sociodemographic county data from the United States Census Bureau's American Community Survey (ACS) were input into the model of PA spending. ACS data for these years are only available from the 5-year rolling census product. The Hazards and Vulnerability Research Institute's (HVRI, 2016a) set of social vulnerability indicators (Social Vulnerability Index [SoVI®]) served as the basis for model inputs. These indicators represent a set of socioeconomic, demographic, and built environment variables drawn from historical disaster case study literature (Cutter et al., 2003). Together, these variables provide a snapshot of social vulnerability to environmental hazards and disasters. A full description of how each indicator specifically relates to social inequality and increases the risk of harm from disaster descriptions can be found here: http://artsandsciences.sc.edu/geog/hvri/faq. Social vulnerability variables and ranges for each year are listed in Table 1. Variables were standardized and then recoded into three categories using the same standard deviation classification scheme discussed above. Table 2 depicts an example of the coding scheme.

Control Variables

A property loss variable from the Hazards and Vulnerability Research Institute's (HVRI, 2016b) SHELDUS™ database was utilized as a control for disaster event severity. SHELDUS contains value added information on property and crop losses for 18 different event types in the United States from 1960 to present at the county level. Importantly, SHELDUS is the only disaster data set currently available containing aggregated damage and loss estimates adjusted for inflation across the whole United States at the county level (Gall, Borden, & Cutter, 2009). SHELDUS is built upon raw data obtained mainly from the National Oceanic and Atmospheric Administration's National Climatic Data Center, U.S. Geological Survey, and the U.S. Department of Agriculture. Raw data are aggregated to the county level, and the amount of damage produced from each event is adjusted for inflation. Loss totals, in the form of property damage, for each year and every county included in federally declared disasters were also utilized in creating a per capita loss measure. This per capita loss variable was logged to the base 10, and (as above) recoded into low, medium, and high categories based on standard deviations as a model control.

A control variable for FEMA region was also included in all models. FEMA utilizes 10 regional offices each overseeing disaster operations across a number of states. These regional offices work closely with state and local governments and may be a source of variation in PA fund allocations. Furthermore, because certain regions may be associated both with costly disasters, such as hurricanes, and certain demographic characteristics, including this control minimizes the chance of biased results.

Finally, the number of federally declared disasters occurring in each county and year, total county population, and total number housing units in each county were included as controls. These control variables further reduce model bias and ensure relationships between the social vulnerability indicators and PA spending are accurately depicted.

Analytic Strategy

A multinomial logistic regression (MLR) is employed to identify influential relationships between government spending, social vulnerability variables, and control variables. The MLR model is an extension of binary logistic regression and produces two sets of coefficients (eß) expressed as odds ratios that are compared with a reference outcome. Here, the dependent variable is coded as high, medium, or low funding based on a standard deviation classification to decrease potential bias associated with arbitrary numerical differences in funding levels. The reference outcome was set to the "low funding category" meaning that all model results illustrate a comparison with low levels of PA funding. Utilizing a similar procedure for recoding the social vulnerability inputs enabled direct comparison of counties with high and medium amounts of PA to those with low amounts of PA in respect to low, medium, or high levels of the social vulnerability indicators. For the social vulnerability indicators, the reference variable was set to the "high vulnerability category," enabling easy identification of funding levels for counties with lower levels of socially vulnerable populations compared with counties with high levels of socially vulnerable populations.

Table 1. List of SoVI® Variables and Ranges for Each Year and Category.

SoVI® variables	Description	2012 ranges			2013 ranges			2014 ranges			2015 ranges		
		Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Median gross rent	Median gross rent for renter–occupied housing units	373-652	653-909	912-1,678	332-561	562-738	739-1,566	328-585	586-744	748-1,548	351-581	582-749	750-1,609
Median age	Median age	21-37	38-42	43-57	22-38	39-43	44-57	22-37	38-42	43-55	26-38	39-42	43-55
Median house value	Median dollar value of owner–occupied housing units	33,900-120,900	120,901-237,500	237,501-944,100	485,00-90,200	90,201-162,200	162,201-665,300	54,500-91,400	91,401-147,300	147,301-510,300	33,500-85,000	85,001-153,500	153,501-902,500
Per capita income	Per capita income	11,181-21,553	21,554-29,116	29,117-61,779	10,498-22,329	22,330-27,721	27,722-50,839	10,806-21,126	21,127-26,429	26,430-48,025	11,039-20,671	20,672-25,852	25,853-46,248
People per unit	Average number of people per household	1.95-2.44	2.45-2.64	2.65-3.37	1.96-2.33	2.34-2.57	2.58-4.39	2.04-2.39	2.4-2.62	2.63-4.59	2.06-2.43	2.44-2.63	2.64-3.84
Age dependent populations	%Population aged under 5 years or 65 years and over	11.84-19.52	19.53-23.01	23.02-37.9	14.57-21.39	21.41-24.94	24.95-36.81	15.12-21.09	21.10-24.56	24.57-39.09	12.5-21.51	21.52-24.96	24.97-40.17
Asian populations	%Asian population	0-0.15	0.16-3.55	3.56-34.02	—	0-2.13	2.14-32.3	—	0-2.37	2.38-26.13	0-0.13	0.14-1.61	1.62-15.51
Black populations	%African American (Black) population	0-4.92	4.93-21.05	21.06-86.19	—	0-6.56	6.57-70.29	0-1.81	1.82-17.97	17.98-73.92	0-0.99	1.00-11.52	11.53-65.47
Unemployment	%Civilian labor force unemployed	10.35-23.14	23.15-31.8	31.81-61.11	9.06-18.59	18.6-26.48	26.49-54.98	8.93-20,358	20.59-30.18	30.19-57.71	7.91-23.95	23.96-33.24	33.25-61.69
Educational attainment	%Population over 25 years of age with less than 12 years education	2.55-12.6	12.61-19.14	19.15-38.12	3.02-10.09	10.1-15.08	15.09-34.24	3.45-11.17	11.18-17.42	17.43-36.91	3.45-12.5	12.51-19.17	19.18-53.72
English proficiency	%Population speaking English with limited proficiency	0-1.12	1.13-5.36	5.37-28.19	0-1.09	1.1-4.45	4.46-21.34	0-0.98	0.99-3.85	3.86-18.47	0-0.95	0.96-5.34	5.35-51.43
Extractive employment	%Employment in extractive industries	0-1.8	1.9-6.0	6.1-25.5	.1-4.1	4.2-11.2	11.3-46.8	.1-3.1	3.2-9.5	9.6-49.9	.1-3.6	3.7-9.9	10-37.3
Family composition	%Children living in married couple families	28.08-63.78	63.79-73.65	73.66-89.8	35.31-68.05	68.06-76.54	76.55-100	28.2-64.49	64.5-74.86	74.87-95.99	38.14-66.03	66.04-74.32	74.33-93.72
Gender	%Female	33.78-49.18	49.19-51.54	51.55-55.73	35.14-48.88	48.89-50.82	50.83-53.31	40.64-49.57	59.58-51.10	51.11-54.98	33.65-48.91	48.92-51.22	51.23-55.19
Gendered employment	%Female participation in the labor force	38.81-46.44	46.45-49	49.01-63	37.4-45.83	45.84-48.26	48.27-63.55	37.56-45.99	46-48.59	48.6-56.22	29.81-45.43	45.44-47.96	47.97-59.16
Female-headed households	%Families with single female-headed households	3.31-10.35	10.36-14.42	14.43-31.47	1.29-7.98	7.99-11.41	11.42-26.26	1.22-8.95	8.96-13.66	13.67-32.61	2.49-9.56	9.57-13.06	13.07-24.4
Hispanic populations	%Hispanic population	0-1.91	1.92-8.79	8.8-53.52	0-1.32	1.33-12.1	12.11-81.66	0-0.9	0.91-9.83	9.84-76.94	0-2.15	2.16-15.01	15.02-98.71
Mobile homes	%Population living in mobile homes	0-7.66	7.67-18.04	18.05-49.19	0-6.16	6.17-13.69	13.7-42.17	0.11-7.73	7.74-17.61	17.62-42.75	0.04-10.3	10.4-19.27	19.28-46.8
Native American populations	%Native American population	—	0-1.46	1.47-17.76	—	0-6.91	6.92-90.43	—	0-6.53	6.54-88.84	—	0-3.76	3.77-48.5
Automobile access	%Housing units with no car available	1.67-4.59	4.6-10.86	10.87-78.3	0-3.74	3.75-8.45	8.46-83.66	0.91-4.01	4.02-9.25	9.26-82.49	0.62-4.76	4.77-7.9	7.91-44.04
Special needs populations	%Population living in nursing facilities	0-0.44	0.45-0.8	0.81-2.52	0-0.64	0.65-1.19	1.2-4.92	0-0.55	0.56-1.05	1.06-2.98	0-0.53	0.54-0.97	0.98-2.69
Poverty	%Persons living in poverty	3.53-12.56	12.57-19.25	19.26-42.64	4.38-11.86	11.87-17.71	17.72-47.98	4.36-13.37	13.38-20.09	20.1-44.33	4.62-14.53	14.54-20.7	20.8-42.99
Renter populations	%Renter–occupied housing units	5.93-18.8	18.81-27.63	27.64-73.99	4.96-18.7	18.71-25.46	45.47-59.01	5.99-19.81	19.82-26.12	26.13-43.71	4.26-19.87	19.88-26.46	26.47-59.43
Wealth	%Families earning more than US$200,000 per year	0-1.47	1.48-5.03	5.04-23.24	0-1.46	1.47-3.57	3.58-17.04	0-1.35	1.36-3.24	3.25-18.3	0-1.41	1.42-3.34	3.35-14.37
Service employment	%Employment in service occupations	9.65-16.72	16.73-20.4	20.41-32.63	7.22-16.25	16.28-19.58	19.59-32.55	8.3-16.11	16.12-19.35	19.36-32.43	9.11-16.4	16.41-19.59	19.6-32.25
Social security beneficiaries	%Households receiving Social Security benefits	13.19-29.89	29.9-37.37	37.38-56.39	13.48-31.46	31.47-37.9	38-63.17	16.82-32.04	32.05-38.58	38.59-59.84	16.2-33.72	33.73-40.43	40.44-65.44
Housing unit occupancy	%Unoccupied housing units	1.97-11.59	11.6-21.8	21.81-66.27	4.21-12	12.1-22.15	22.16-65.88	4.04-11.98	11.99-20.45	20.46-53.69	4.56-13.22	13.23-21.64	21.65-66.65
Health insurance	%Population without health insurance	3.17-11.81	11.82-16.48	16.49-38.28	2.52-10.06	10.07-15.69	15.7-39.37	4.86-10.86	10.87-16.09	16.1-44.46	2.21-11.76	11.77-16.78	16.79-37.61
Health care access	Community hospitals per capita	—	0.000005-0.0002	0.00021-0.0035	—	0.000004-0.00078	0.00079-0.019	0.000007-0.00002	0.000021-0.0007	0.00071-0.009	—	0.000004-0.00037	0.00038-0.004

Note. SoVI = Social Vulnerability Index

Table 2. Example of Coding Scheme Using Ascension Parish, Louisiana, Part of the Federal Disaster Declaration for Hurricane Isaac.

Variable	Value in 2012	*SD*s below or above mean for all counties in 2012	Recoded value
%Hispanic population	4.56	.11 *SD* below mean	“2” medium
Per capita PA funds in dollars	17.69	.63 *SD* above mean	“3” high

Note. PA = public assistance.

Table 3. MLR Model Fit and Pseudo R^2 Information.

Model	Input count (counties)	Chi-square model fit (intercept-final)	Degrees of freedom	Nagelkerke pseudo R^2	Confidence level
2012	437	347.021**** (939.752-592.731)	142	.62	99% ± 5.73
2013	565	294.624**** (1,226.497-931.873)	140	.459	99% ± 4.92
2014	438	400.453**** (948.777-548.324)	140	.677	99% ± 5.72
2015	659	389.343**** (1,446.392-1,057.049)	144	.502	99% ± 4.47
2012-2015	2,099	684.150**** (4,570.964-3,886.815)	152	.314	99% ± 1.62

Note. MLR = multinomial logistic regression.
*$p < .05$. **$p < .01$. ***$p < .005$. ****$p < .001$.

This categorization enables a more refined analysis into driving forces between low, medium, and high levels of spending as they relate to similar classifications of social vulnerability variables.

Results were analyzed using a two-part strategy. One MLR model for each year in the analysis (2012-2015) identified those social vulnerability indicators driving PA funding per capita (herein referred to as funding). A final model focused on all the data over the 4-year span, controlling for year. This model identified overall social vulnerability effects on PA funding from 2012 to 2015. For each MLR model, two sets of coefficients are produced and described in the following sections. One set of coefficients depict the association between the social vulnerability variables and the odds of a county receiving medium amounts of PA funding, compared with the odds of that county receiving low amounts of PA funding. Similarly, the second set of coefficients depicts associations between the social vulnerability indicators and the odds of receiving high PA funding compared with low funding. Data standardization, normalization, and model development were undertaken using IBM SPSS 25 and Stata 14.1.

Results

Understanding sociodemographic influences across all years (2012-2015) as well as within any given year was a main goal of this work and required five MLR models. As such, results will be discussed first of each individual annual model and then of the model for all years, so that patterns of socioeconomic influence can be more easily identified and discussed. Results for each year (Tables 4-8) include significant drivers of funding and are grouped into two categories; those negatively influencing (decreasing) likelihood of funding receipt and those positively influencing (increasing) likelihood of medium to high funding receipt. In addition, each driver is categorized as either exemplifying equity or inequity in Tables 4-8. We refer to cases as instances of exemplary equity (identified by †) when a higher level of a social vulnerability driver increases the likelihood of higher levels of PA funding. We define the converse as cases of procedural inequities (identified by ‡) and identify the social vulnerability drivers that decrease the likelihood of PA funding as they increase. Finally, those variables seen as modifiable through local decisions, programs, or policies were identified for further discussion and analysis (identified by L).

Chi-square goodness of fit statistics across all models show significance at the .001 level indicating a very high model fit for each of the years individually and the composite (2012-2015). Table 3 shows the number of inputs, chi-square significance, Nagelkerke psuedo R^2, and confidence interval for each data set. Nagelkerke psuedo R^2 is reported here because the R^2 is not reported in MLR. Furthermore, R^2 indicates the proportion of the variability in the dependent variable that is explained by the model. Psuedo R^2 is neither directly comparable with the R^2 for ordinary least squares (OLS) models nor can it can be interpreted in the same fashion as R^2. Rather, pseudo R-squared measures are relative measures indicating how well the model explains the data. The following value classifications for our pseudo R^2 values were utilized: <.3 (no or very weak model explanation), .3-.5 (weak model explanation), .5-.7 (moderate model explanation), and >.7 (strong model explanation), adapted from Moore and Kirkland (2007).

Table 4. Influential Sociodemographic Variables From the 2012 Multinomial Regression Model.

2012 model	Public assistance funds per capita	
Nagelkerke pseudo R^2 = .602	Medium	High
Negative influences—variables decreasing the likelihood of a county to receive public assistance funds		
Low per capita losses†L	86.46%****	95.08%****
Medium per capita losses†L	74.9%***	94.49%****
Medium % of age-dependent population†	74.41%*	
Low % female population†	81.45%*	
Medium % female population†	71.92%**	
Low % employment in service industry†L	68.45%*	
Low % population without automobile†L		88.06%*
Low % poverty population†L		87.69%*
Low % children in two-parent families‡		86.17%*
Medium % children in two-parent families‡	67.55%*	81.43%**
Medium number of hospitals per capita†L		78.69%*
Positive influences—variables increasing the likelihood of a county receiving public assistance funds		
Medium % Hispanic population‡	753%**	825%*
Low % nursing home residents‡		348%*
Medium median gross rent†L		1,022%***
Low % population without health insurance‡L	361%*	

Note. † = exemplary equity; L = locally modifiable; ‡ = inequity.
*p < .05. **p < .01. ***p < .005. ****p < .001.

Table 5. 2013 Multinomial Regression Model.

2013 model	Public assistance funds per capita	
Nagelkerke pseudo R^2 = .459	Medium	High
Negative influences—variables decreasing the likelihood of a county to receive public assistance funds		
Low per capita losses†L	52.52%*	75.15%****
Medium per capita losses†L	47.78%*	70.39%****
Low % population without automobile†L	74.47%*	
Low % children in two-parent families‡	65.52%*	
Positive influences—variables increasing the likelihood of a county receiving public assistance funds		
Medium % female labor force participation‡L	96%*	
Low % female population‡		243%*
Low per capita income†L		622%*
Medium % unemployment‡L		220%*

Note. † = exemplary equity; L = locally modifiable; ‡ = inequity.
*p < .05. **p < .01. ***p < .005. ****p < .001.

2012 Model

Identifying those socioeconomic indicators influencing receipt of PA funds per capita (funding) in 2012 while controlling for FEMA region, number of disasters, total population, and total housing resulted in a significant and moderately explanatory model (pseudo R^2 = .620) with numerous influential independent variables. Specifically, 15 variables (Table 4) have significant influence on medium to high county-level funding receipt. As expected, per capita disaster losses in a county is one of the most significant indicators of receiving more funding. In 2012, counties were less likely to receive medium or high funding if they had lower disaster losses (86.46% and 74.9% less likely, respectively) than if they had higher disaster losses. In addition, counties were less likely to receive medium funding under a variety of different scenarios, including: counties were 81.45% and 71.92% less likely to receive medium funding when they had low or medium percentages of female populations compared with those with high percentages. Counties were 74.14% less likely to receive medium funding when they had medium percentages of age-dependent populations compared with those with high percentages. They were 68.45% less likely to receive medium funding when they had low percentages of people employed in service sector positions compared with

Table 6. Influential Sociodemographic Variables From the 2014 Multinomial Regression Model.

2014 model	Public assistance funds per capita	
Nagelkerke pseudo $R^2 = .677$	Medium	High
Negative influences—variables decreasing the likelihood of a county to receive public assistance funds		
Low per capita losses†L	81.95***	92.27%****
Medium per capita losses†L	80.12%***	94%****
Medium % Asian population†	88.66%*	—
Low % unoccupied housing units†L	—	84.97%*
Medium % unoccupied housing units†L	—	79.63%*
Medium number of people per unit†L	70.72%*	80.48%*
Low % employment in extractive industry†L	87.58%*	95.88%***
Medium % employment in extractive industry†L	—	89.72%**
Low % employment in service industry†L	—	82.53%**
Medium % employment in service industry†L	—	71.66%*
Low % female-headed households†	98.43%****	97.37%**
Medium % female-headed households†	91.53%***	87.5%*
Low % mobile homes†L	88.11%**	—
Positive influences—variables increasing the likelihood of a county receiving public assistance funds		
Low % Black population‡	780%*	—
Medium % Black population‡	1,218%***	1,032%*
Medium % Native American population‡	746%*	1,316%*
Low % Social Security beneficiaries‡	—	5,972%****
Medium % Social Security beneficiaries‡	—	433%*
Low % children in two-parent families†	—	965%*
Low % unemployment‡L	2,909%***	—
Low median gross rent†L	1,075%**	—

Note. † = exemplary equity; L = locally modifiable; ‡ = inequity.
*$p < .05$. **$p < .01$. ***$p < .005$. ****$p < .001$.

Table 7. Influential Sociodemographic Variables From the 2015 Multinomial Regression Model.

2015 model	Public assistance funds per capita	
Nagelkerke pseudo $R^2 = .502$	Medium	High
Negative influences—variables decreasing the likelihood of a county to receive public assistance funds		
Medium per capita losses†L	—	52.53%*
Medium % of age-dependent population†	—	59.89%*
Low % employment in extractive industry†L	—	71.22%*
Low % population without automobile†L	73.76%**	78.16%**
Medium % of people with no automobile†L	60.1%*	63.51%*
Low median gross rent‡L	80.77%*	83.23%*
Medium median gross rent‡L	64.83%*	—
Medium % population without health insurance†L	69.04%*	74.69%*
Positive influences—variables increasing the likelihood of a county receiving public assistance funds		
Low % renter population‡L		355%**
Low % mobile homes‡L		186% *

Note. † = exemplary equity; L = locally modifiable; ‡ = inequity.
*$p < .05$. **$p < .01$. ***$p < .005$. ****$p < .001$.

those with high percentages. Finally, counties with lower percentages of children in two-parent families were 67.55% less likely to receive medium levels of funding compared with counties with higher percentages of children living with two parents.

The drivers of high funding overlap slightly with those predicting medium levels. Per capita losses was highly influential in both models. Counties with low and medium adjusted losses were respectively 95.08% and 94.49% less likely receive high PA funding compared with counties with

Table 8. Influential Sociodemographic Variables From the 2012-2015 Multinomial Regression Model.

Model for all years, 2012-2015	Public assistance funds per capita	
Nagelkerke pseudo R^2 = .314	Medium	High
Negative influences—variables decreasing the likelihood of a county receiving public assistance funds		
Low per capita losses†L	56.34%****	60.37%****
Medium per capita losses†L	46.83%****	72.56%****
Low % unoccupied housing units†L	—	41.69%*
Low % employment in extractive industry†L	—	54.12%***
Low % population without automobile†L	57.18%***	55.58%**
Medium % population without automobile†L	41.85%**	46.11%**
Positive influences—variables increasing the likelihood of a county receiving public assistance funds		
Year = 2012	223%****	197%****
Year = 2014	57%*	—
Low % female population‡	—	79%*
Low % renter population‡L	—	130%***

Note. † = exemplary equity; L = locally modifiable; ‡ = inequity.
*p < .05. **p < .01. ***p < .005. ****p < .001.

high loss levels. In addition, counties were less likely to receive high funding levels when they had low percentages of people without access to automobiles (88.06% less likely) compared with those with high percentages, when they had low percentages of poverty (87.69% less likely) compared with those with high percentages, when they had low or medium percentages of children in two-parent families (86.17% and 81.43% less likely) compared with those with high percentages, or when they had a medium number of hospitals per capita (78.69%) compared with those with a high number of hospitals per capita.

Conversely, certain socioeconomic variables were positive influences on per capita receipt. Four variables significantly predicted per capita fund receipt in 2012. Counties with medium percentages of Hispanic populations were 753% and 825% more likely to receive medium or high funding, respectively, when compared with counties with a high percentage of Hispanic populations. In addition, counties with low percentages of nursing home residents were 349% more likely to receive high funding than those with high percentages of nursing home residents. Interestingly, counties in the middle category of median gross rent are 1,022% more likely to receive high funding compared with counties in the highest gross rent category. Finally, those counties with low percentages of populations without health insurance are 361% more likely than counties with high percentages of people without health insurance to receive high funding.

2013 Model

A slightly lower model fit (Table 5) for the 2013 MLR yields a smaller set of drivers varying in significance levels. Two sociodemographic characteristics were highly influential in predicting medium and high funding levels across the study area, and an additional two variables were predictive of medium funding levels (Table 5). Like the 2012 models, counties with low per capital losses were 52.53% and 75.15% less likely than counties with high per capita losses to receive medium and high funding, respectively. Furthermore, counties with low and medium per capita losses were 47.78% and 70.39% less likely to receive medium and high funding compared with counties with high per capita losses. Additionally, counties with low percentages of people with no automobile were 74.47% less likely to receive medium funding than counties with high percentages of people without automobile access, and counties with low percentages of children in two-parent families were 65.52% less likely than counties with high percentages to receive medium funding.

Conversely, a set of positive influences on funding receipt are also reported by the MLR model. Here, counties with medium percentages of female labor force participation were 96% more likely to receive medium funding when compared with counties with high percentages of female labor force participation. In addition, counties with low percentages of female populations were 243% more likely to receive high funding compared with counties with high percentages of female populations. Interestingly, counties with lower per capita incomes were 622% more likely to receive high funding compared with counties with high per capita incomes. Finally, those counties with only medium percentages of unemployment were 220% more likely than counties with high percentages of unemployment to receive high funding.

2014 Model

MRL model significance at the .001 level and pseudo R^2 (.677) indicate strong explanatory power of the socioeconomic drivers on funding receipt (or lack thereof). Significantly more variables (21) were kept in the model for this year, 13 negative influencers on funding receipt, and 8 positive influencers (Table 6). As in other years, both low and medium per capita losses were strong negative influences on funding receipt. Here, counties with low per capita losses were 81.95% less likely to receive medium funding and 92.27% less likely to receive high funding than counties with high per capita losses. Moreover, counties with medium per capita losses were 80.12% less likely to receive medium funding and 94% less likely to receive high funding than counties with high per capita losses. Multiple additional driving variables are uncovered with this MLR when controlling for all other factors. Counties were less likely to receive medium funding when they had medium numbers of people per unit (70.72% less likely) compared with those with high numbers of people per unit, low percentage of people employed in extractive industry (87.58% less likely) compared with those with high percentages, low or medium percentages of female-headed households (98.43% and 91.53% less likely, respectively) compared with those with high percentages, or they had low percentages of mobile homes (88.11% less likely) compared with those with high percentages. Furthermore, many variables negatively influenced receipt of high levels of funding. Here, counties were less likely to receive high levels of funding when they had low or medium percentages of unoccupied housing units (84.97% and 79.63% less likely) than counties with high percentages; medium numbers of people per unit (80.48% less likely) than counties with high number of people per unit; low or medium percentages of people employed in extractive industry (95.88% and 89.72% less likely, respectively) compared with counties with high percentages of primary sector employees; low or medium percentages of service sector employees (82.53% and 71.66% less likely, respectively) compared with counties with high percent service industry workers, or low or medium percentages of female headed households (97.37% and 87.57% less likely, respectively) compared with counties with high percentages.

Conversely, MRL results identify numerous positive influences on funding receipt. Here, counties were more likely to receive medium levels of funding when they had low or medium percentages of Black populations (780% and 1,218% more likely, respectively) compared with counties with high percentages; medium percentages of Native American populations (746% more likely) than those with high percentages; low percentages of unemployed populations (2,909% more likely) compared with counties with high percentages; or lower median gross rent (1,075% more likely) than counties with higher median gross rent. Certain variables were also highly predictive of high funding levels. Counties were more likely to receive high funding if they had medium percent Black populations (1,032% more likely) compared with counties with high percentages and medium percentages of Native American populations (1,316% more likely) compared with counties with high percentages. In addition to these, counties were more likely to receive high funding when they had low or medium percentages of social security beneficiaries (5,972% and 433%, respectively) compared with counties with high percentages. Finally, counties were 965% more likely to receive high funding when they had low percentages of children in two-parent families compared with counties with higher percentages.

2015 Model

A middle of the road model fit (Naglekerke pseudo $R^2 = .502$) for 2015 yielded a smaller set of drivers varying in significance levels. Ten sociodemographic characteristics were highly influential in predicting medium and high funding across the study area (Table 7). Contrasting other models, per capita losses was not a predictor of medium funding. Rather, counties with low and medium percentages of people with no automobile were less likely (73.76% and 60.1%, respectively) to receive medium funding and less likely (78.16% and 63.51%, respectively) to receive high funding than counties with high percentages of populations without automobile access. Furthermore, low gross rents made counties 80.77% and 83.23% less likely to receive medium and high funding, respectively, than counties with high gross rents, and counties with medium gross rents were 64.83% less likely than those with high gross rents to receive medium funding. Moreover, counties with medium percentages of populations without health insurance were 69.04% and 74.69% less likely to receive medium and high funding, respectively, compared with counties with high percentages without health insurance coverage. Finally, medium per capita losses made counties 52.53% less likely, medium percentages of age-dependent populations made counties 59.89% less likely, and low percentages of primary sector employment made counties 71.22% less likely to receive high funding levels compared with counties with higher values across these measures.

Only two variables provided a positive influence on high funding in this model. Here, counties with low percentages of renters were 355% more likely to receive high funding than counties with high percentages of renters and counties with low percentages of mobile homes were 186% more likely to receive high funding than counties with high percentages.

All Years (2012-2015) Model

A MRL model utilizing all years of data produced a weak model fit (Naglekerke pseudo $R^2 = .314$) with nine significant predictive variables (Table 8). Mirroring most yearly models, counties with low or medium per capita losses were 56.34% and 46.83% less likely, respectively, than counties with high per capita losses to receive medium funding and 60.37% and 72.56% less likely, respectively, to receive high levels of funding. In addition, counties with low or medium percentages of populations without automobile access were

57.18% and 41.85% less likely, respectively, than counties with high percentages without automobile access to receive medium funding and 55.58% and 46.11% less likely, respectively, to receive high funding. Furthermore, counties characterized by low percentages of unoccupied housing units were 41.69% less likely than those with high percentages to receive high funding and counties with low percentages of primary sector employment were 54.12% less likely than those with high percentages to receive high funding.

Conversely, counties impacted by disasters in 2012 were 223% and 197% more likely to receive medium and high PA funding compared with those experiencing impacts in 2015 and counties impacted in 2014 were 57% more likely to receive medium funding. In addition, counties with low female population percentages were 79% more likely to receive high funding compared with those with high female population percentages and those with low percentages of renters were 130% more likely than those with high percentages to receive high levels of funding.

Discussion

The aim of this analysis was to identify how inequalities manifest themselves in association with a suite of underlying socioeconomic and demographic characteristics. Accordingly, the following research questions guided our analysis:

> **Research Question 1:** Are social indicators of vulnerability associated with lower amounts of PA spending in counties with similar levels of damage?
>
> **Research Question 2:** What are the most influential social vulnerability indicators?

Results support the first study hypothesis; the models identified a range of demographic, environmental, and socioeconomic conditions as being significantly related to aid distribution, signaling that factors above and beyond total losses influence funding and result in disparate levels of recovery across counties. Interestingly, results indicated less support for the second hypothesis; there were fewer consistencies across the years studied in terms of socioeconomic and demographic drivers of aid distribution among counties. Across all years and models, there were 60 different drivers of per capita PA receipt. Only seven variables increased the likelihood of greater fund distribution across more than a single model including per capita loss, %employment in extractive industry, %without automobile, %service sector employment, %unoccupied housing, and %age-dependent populations. In addition, only one of the 21 drivers associated with decreased likelihood of funding (%children in two-parent families) was significant in more than one year.

The key points drawn from findings here include (a) total losses influenced PA funding in every model, (b) while social vulnerability characteristics also influenced PA spending across all years, no specific indicators were consistently significant, and finally (c) each regression model identified various combinations of driving factors both proving exemplary equity and procedural inequality (Tables 4-8). Thirty-nine drivers (identified in Tables 4-8 by "†") highlighted some of the ways in which funding is *equitably* distributed, meaning that there was successful program delivery through an equity lens when controlling for losses. However, 21 drivers (identified by ‡) pinpointed opportunities for either federal government or state/local PA recipients to build more equity in fund distribution and were denoted as procedural inequities.

Figure 2 depicts the ratio of equitable to inequitable funding distributions over the study years. The 2012 model identified only 5 instances of significant procedural inequality and 10 cases of exemplary equity, a 67/33 split between "successful" program delivery and possible areas of improvement. Comparing 2012 with a 50/50 split between exemplary equity and procedural inequity for 2013 indicates a system not built to account for procedural inequities systematically. 2014 had the highest ratio in favor of exemplary equity (71% across 15 variables) compared with (29% over six variables) procedural inequality. 2015's equity ratio 10:5 mirrors that of 2013, proving no specific trend in process improvements across the years. Although each of these cases show more positives than negatives, one should understand that these do not cancel each other out. Even one instance of inequitable recovery fund distribution should be considered problematic and corrected by either FEMA or the local emergency management entities applying for these grants.

These findings indicate that FEMA's PA program generally operates as designed (e.g., places with the highest losses receive the most funding). However, because each model output also identified a program delivering less support for socially vulnerable counties when accounting for total losses, we argue that the PA program could be delivered in a more equitable manner. Of the drivers identified in the analysis, many are consistent with environmental and disasters inequality research that links race, socioeconomic status, gender, and age with disparities in recovery (Bullard & Wright, 2012; Thomas et al., 2013), however, the absence of consistent indicators across the years indicate that inequities manifest themselves in dissimilar ways. For example, in 2012 (the year of Superstorm Sandy), the model identified inequity in counties based on Hispanic populations, nursing home residents, and populations without health insurance. In 2013, counties with higher percentages of men and those without high unemployment were more likely to receive higher levels of funding and counties with high percentages of children in single-parent families received lower levels of funding. Race (%Black and %Native American), age (social security beneficiaries), and employment negatively influenced fund distribution in 2014. In 2015, counties with lower renter and mobile home percentages were more likely to receive funds. Although we are not arguing that

Figure 2. Number and percentage of instances showing exemplary equity and procedural inequality across model years.

these inequities are not necessarily intentional instances of discrimination, results show that social vulnerability indicators have an effect on the distribution of funding. These social effects constitute procedural inequities, and these procedural inequities may be the result of numerous mechanisms, as for example, counties with high levels of Hispanic residents may be characterized by heightened language barriers that decrease municipalities technical capacity to apply for PA. To address these mechanisms, we offer a set of recommendation in the following section.

Recommendations for Public Administration

In all, results show that social factors matter for how aid is distributed in counties with similar levels of damages, underscoring the complexities of administrative processes as social (as well as technical) endeavors. Thus, we argue that a wide range of social vulnerability factors should be more robustly incorporated into decision-making processes about funding allocation to prevent disparities, and we recommend that public administration scholars focus on a wider array of variables than those traditionally associated with county capacity for emergency management functions (i.e., socioeconomic indicators) for addressing procedural equity. Here, focusing on all indicators of social vulnerability will also be valuable in ensuring equitable disaster recovery. Doing so will provide a unique and more holistic perspective on where inequities might occur and facilitate opportunities for targeting solutions. For example, researchers understand that residents in nursing homes are susceptible to great harm in disasters because care facilities are often ill-equipped to withstand major disruption (Peek, 2013). Failing to ensure PA to restore and rebuild care facilities would further exacerbate the hazards older adults are exposed to.

In line with findings concerning the need for effective government over outdated traditions (Kettl, 2006), and coordinated action among disaster response and recovery actions (Nowell et al., 2018), we suggest that FEMA consider a robust characterization of communities utilizing a suite of socioeconomic characteristics rather than depending on only one variable (losses). We also suggest public administrators initiate targeted technical assistance programs to municipalities with high levels of social vulnerability. Programs may also be focused on certain types of institutions (such as nonprofits, hospitals, or nursing homes) that serve vulnerable populations. Furthermore, the building of local, regional, and national programs to reduce levels of social vulnerability before disaster strikes could also alleviate potential inequities. Because all disaster preparedness, response, and recovery planning start at the local level, building and sustaining programs aimed at helping all residents better prepare for, respond to, and rebound from disasters are critical. A majority of variables (66% designated with an "L" in Tables 4-8) influential in PA fund receipt can be directly modified by local, region, state, and national programs aimed at decreasing vulnerability, that is, programs could have the dual purpose of decreasing hazardous exposures and preventing inequality formation. Although some of the identified inequities (e.g., lack of health insurance or poverty) are being addressed at the national level, these and others (e.g., lack of access to automobiles, unemployment, renter populations) should also be adopted as priorities at all levels of government, nonprofit, and private sectors. Furthermore, an enhanced commitment to vulnerability reduction and capacity-building programs enhances stakeholder ability to participate in predisaster recovery planning, further reducing the likelihood of disparities in the wake of disaster. Moving forward with these recommendations will not only have direct benefit in ensuring equitable disaster recovery but will also build communities better able to withstand future disasters.

Conclusions, Caveats, and Future Directions

This analysis utilized a procedural equity lens in understanding how FEMA's PA program currently operates, addressing whether PA spending was equitably distributed across counties with varying levels of social vulnerability in the years 2012-2015. Social characteristics most influential in funding distribution were identified for each year and across all years and provided evidence that inequities do exist across impacted counties. However, although inequities did exist during the years investigated, there were also many instances of exemplary equity, where those most vulnerable were receiving more aid than those less vulnerable. Results indicate that FEMA's PA program operates well when considering damages in that higher damages were associated with higher spending. However, the varying occurrences of inequitable funding distribution indicates that more attention can be placed on programmatic measures to address disaster recovery in counties with more socially vulnerable populations.

Importantly, the analysis evidences how disaster assistance programs may limit the benefits to particular places and groups of people, especially when these people and places are in the most need of resources in recovery. This finding contributes to a growing body of research that aims to identify and address sources of inequitable recovery following disasters (e.g., see Verchick, 2012). Furthermore, equity research to date has generally focused on univariate relationships between outcome measures and population characteristics, however, these results demonstrate an imperative to consider wider socioeconomic, demographic, and built environment characteristics as drivers of procedural inequities in funding. The results also identify many instances of exemplary equity and can be used to further elaborate on and institutionalize measures to ensure equitable funding allocations into the future.

Before concluding, we would like to recognize limitations to the study, and we also suggest several directions for further research. First, we rely on the assumption that disaster assistance funding for public infrastructure does indeed benefit a diverse public. This assumption should also be subject to some scrutiny, but given the extent to which major disasters disrupt social systems and given the types of funds granted through this program—immediate threat response support, funds for recovery from sustained damages, and funding for disaster mitigation at specific impact locations—we believe the vast majority of funding for public infrastructure is of critical importance to communities, especially communities with vulnerable populations (Bolin & Kurtz, 2018). However, we want to acknowledge that more fine-grained analysis can pinpoint the circumstances under which public infrastructure repairs and critical mitigation efforts may disproportionally benefit some members of the community over others. Furthermore, as with many studies across geographical locations, there may be differences in study findings depending on the spatial scale deployed as the unit of analysis. Thus, results imply a need for more highly resolved and temporally complete research in identifying specific PA programmatic elements requiring modification to allocate funds more equally. Future analysis could focus on differences in PA spending allocations within particular disasters or across particular disaster types. For example, inequities were particularly pronounced in 2012, the year of Super Storm Sandy and further studies could identify and test the mechanisms through which social factors impact equity across this specific site. Consequently, more fine-grained analyses would allow for exploring disaster spending in U.S. territories—such as Puerto Rico after Hurricane Maria—to further elucidate and redress sources of disparities.

Finally, it should be noted that the purpose of this investigation is to prevent future disparities relating to preevent determinants, and as such, this study does not address all structural drivers of vulnerability and inequality. However, the overall conclusion and recommendation for public administration is still clear: With increased attention to social indicators of vulnerability, governments can better target areas in need of technical assistance, programs for vulnerability reduction, and programs for preevent recovery planning, which will mitigate against inequality formation. In sum, the strong empirical evidence presented here, and elaborated on in past research, gives scholars and practitioners alike reason to critically examine disaster aid distribution and other complex programmatic practices. Drawing upon environmental justice and social vulnerability frameworks presents one way to do so, and this article serves as a starting point for such prerogatives in disaster and public administration research.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This paper was partially supported by funds from the National Science Foundation (1707947), under the Humans, Disasters, and the Built Environment program. This paper was also partially supported by the University of Central Florida's Boardman Endowment for Environmental Science and Public Administration.

ORCID iD

Simone J. Domingue https://orcid.org/0000-0003-0385-3941

References

Bolin, B. & Kurtz, L. (2018). Race, class, and ethnicity. In R. Havidán, D. William & J. E. Trainor (Eds.), *Handbook of disaster research, 2nd Ed*. (pp. 181-203). Cham, Switzerland: Springer.

Bolin, R., & Stanford, L. (2006). *The Northridge earthquake: Vulnerability and disaster*. New York, NY: Routledge.

Bowen, W. M., & Wells, M. V. (2002). The politics and reality of environmental justice: A history and considerations for public administrators and policy makers. *Public Administration Review*, *62*, 688-698.

Bryant, B., & Mohai, P. (1992). *Race and the incidence of environmental hazards*. Boulder, CO: Westview Press.

Bullard, R. D. (2005). *The quest for environmental justice: Human rights and the politics of pollution*. San Francisco, CA: Sierra Book Clubs.

Bullard, R. D. (2008). *Dumping in Dixie: Race, class, and environmental quality*. Boulder, CO: Westview Press.

Bullard, R. D., & Wright, B. (2012). *The wrong complexion for protection: How the government response to disaster endangers African American communities*. New York, NY: University Press.

Burda, M., & Harding, M. (2014). Environmental justice: Evidence from Superfund cleanup durations. *Journal of Economic Behavior & Organization, Part A*, *107*, 380-401.

Cole, L. W., & Foster, S. R. (2001). *From the ground up: Environmental racism and the rise of the environmental justice movement*. New York, NY: New York University Press.

Comfort, L. K., Birkland, T. A., Cigler, B. A., & Nance, E. (2010). Retrospectives and prospectives on Hurricane Katrina: Five years and counting. *Public Administration Review*, *70*, 669-678.

Craemer, T. (2010). Evaluating racial disparities in Hurricane Katrina relief using direct trailer counts in New Orleans and FEMA Records. *Public Administration Review*, *70*, 367-377.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, *84*, 242-261.

Cutter, S. L., & Emrich, C. T. (2006). Moral hazard, social catastrophe: The changing face of vulnerability along the hurricane coasts. *The Annals of the American Academy of Political and Social Science*, *604*, 102-112.

Daley, D. M., & Layton, D. F. (2004). Policy implementation and the Environmental Protection Agency: What factors influence remediation at Superfund sites? *The Policy Studies Journal*, *32*, 375-392.

Durant, R. F., & Rosenbloom, D. H. (2017). The hollowing of American public administration. *American Review of Public Administration*, *47*(7), 719-736.

Elliot, J. R., & Pais, J. (2010). When nature pushes back: Environmental impact and the spatial redistribution of socially vulnerable populations. *Social Science Quarterly*, *9*, 1187-1202.

Federal Emergency Management Agency. (2017). *Public assistance program and policy guidance*. Retrieved from https://www.fema.gov/media-library-data/1496435662672-d79ba9e1edb16e60b51634af00f490ae/2017_PAPPG_2.0_508_FINAL(2).pdf

Finch, C., Emrich, C. T., & Cutter, S. L. (2010). Disaster disparities and differential recovery in New Orleans. *Population and Environment*, *31*, 179-202.

Fothergill, A., Maestas, E. G. M., & Darlington, J. D. (1999). Race, ethnicity and disasters in the United States: A review of the literature. *Disasters*, *23*, 156-173.

Fothergill, A., & Peek, L. A. (2004). Poverty and disasters in the United States: A review of recent sociological findings. *Natural Hazards*, *32*, 89-110.

Fotovvat, H. (2013). Investigation of social based cooperatives on social health of female headed households. *Journal of Social Sciences*, *9*, 146-150.

Gall, M., Borden, K.A., & Cutter, S. (2009). When do losses count?: Six fallacies of natural hazards loss data. *American Meteorological Society*, *90*, 799-809.

Ganapati, E. N. (2012). In good company: Why social capital matters for women during disaster recovery. *Public Administration Review*, *72*, 419-427.

Gooden, S. T. (2015). From equality to social equity. In M. E. Guy & M. M. Rubin (Eds.), *Public administration evolving: From foundations to the future* (pp. 211-231). New York, NY: Routledge.

Gotham, K. (2012). Disasters Inc., privatization and post-Katrina rebuilding in New Orleans. *Perspectives on Politics*, *10*, 633-646.

Gotham, K. F., & Campanella, R. (2011). Coupled vulnerability and resilience: The dynamics of cross-scale interactions in post-Katrina New Orleans. *Ecology and Society*, *16*(3), Article 12. Retrieved from https://www.ecologyandsociety.org/vol16/iss3/art12/

Guy, M. E., & McCandless, S. A. (2012). Social equity: Its legacy, its promise. *Public Administration Review*, *72*, 5-13.

Harrison, J. L. (2011). *Pesticide drift and the pursuit of environmental justice*. Cambridge, MA: MIT Press.

Harrison, J. L. (2014). Neoliberal environmental justice: Mainstream ideas of justice in political conflict over agricultural pesticides in the United States. *Environmental Politics*, *23*, 650-669.

Harrison, J. L. (2016). Bureaucrats' tacit understandings and social movement policy implementation: Unpacking the deviation of agency environmental justice programs from EJ movement priorities. *Social Problems*, *63*, 534-553.

Hazards and Vulnerability Research Institute (HVRI). (2016a). The Social Vulnerability Index, Version 15.2 [Online Database]. Columbia: University of South Carolina. Available from http://www.sovius.org

Hazards and Vulnerability Research Institute (HVRI). (2016b). The Spatial Hazard Events and Losses Database for the United States, Version 15.2 [Online Database]. Columbia: University of South Carolina. Available from http://www.sheldus.org

Holifield, R. (2004). Neoliberalism and environmental justice in the United States Environmental Protection Agency: Translating policy into managerial practice in hazardous waste remediation. *Geoforum*, *35*, 285-297.

Hooks, J. P., & Miller, T. B. (2006). Continuing storm: How disaster recovery excludes those most in need. *California Western Law Review*, *43*, 21-74.

Johnston, B. J., Goerdel, H. T., Lavich, N. P., Jr., & Pierce, J. C. (2015). Social capital and emergency management planning: A test of community context and effects on formal and informal collaboration. *American Review of Public Administration*, *45*, 476-493.

Kettl, D. F. (2006). Is the worst yet to come? *The Annals of the American Academy of Political and Social Science*, *604*, 273-287.

Klinenberg, E. (2002). *Heat wave: A social autopsy of disaster in Chicago*. Chicago, IL: The University of Chicago Press.

Krueger, S., Jennings, E., & Kendra, J. (2009). Local emergency management funding: An evaluation of county budgets. *Journal of Homeland Security and Emergency Management*, *6*(1). doi:10.2202/1547-7355.143

Lavelle, M., & Coyle, M. (1992). Unequal protection: The racial divide in environmental law. *National Law Journal*, *15*, S1-S12S.

Martin, L. L., Levey, M. R., & Cawley, J. (2012). The "new normal" for local government. *State and Local Government Review*, *44*(1_Suppl.), 17S-28S.

Mohai, P., Pellow, D., & Timmons, R. J. (2009). Environmental justice. *Annual Review of Environmental Resources*, *34*, 405-430.

Moore, D. S., & Kirkland, S. (2007). *The basic practice of statistics*. New York, NY: W.H. Freeman.

Morello-Frosch, R. A. (2002). Discrimination and the political economy of environmental inequality. *Environment and Planning C: Government and Policy*, *20*, 477-496.

Morrow, B. H. (1999). Identifying and mapping community vulnerability. *Disasters*, *23*, 1-18.

Muller, C., Sampson, R. J., & Winter, A. S. (2018). Environmental inequality: The social causes and consequences of lead exposure. *Annual Review of Sociology*, *44*, 263-282.

Muñoz, C. E., & Tate, E. (2016). Unequal recovery? Federal resource distribution after a Midwest flood disaster. *International Journal of Environmental Research and Public Health*, *13*, 507-517. doi:10.3390/ijerph13050507

Murphy-Greene, C., & Leip, L. A. (2002). Assessing the effectiveness of Executive Order 12898: Environmental justice for all? *Public Administration Review*, *62*, 679-687.

Norris, F. H., Friedman, M. J., Watson, P. J., & Byrne, C. M. (2002). 60,000 disaster victims speak: Part I. An empirical review of the empirical literature, 1981-2001. *Psychiatry: Interpersonal and Biological Processes*, *65*, 207-239.

Nowell, B., Steelman, T., Velez, A. L. K., & Yang, Z. (2018). The structure of effective governance of disaster response networks: Insights from the field. *The American Review of Public Administration*, *4*, 8699-8715.

O'Neil, S. G. (2007). Superfund: Evaluating the impact of Executive Order 12898. *Environmental Health Perspectives*, *115*, 1087-1093.

Peacock, W. G., Gladwin, H., & Morrow, B. H. (2012). *Hurricane Andrew: Ethnicity, gender and the sociology of disasters*. New York, NY: Routledge.

Peacock, W. G., Van Zandt, S., Zang, Y., & Highfield, W. E. (2014). Inequities in long-term housing recovery after disasters. *Journal of the American Planning Association*, *80*, 356-371.

Pearsall, H., & Pierce, J. (2017). A spoiled well (of data): Addressing the procedural injustice of contemporary environmental justice research through collaborative qualitative data gathering. *Local Environment*, *22*, 388-392.

Peek, L. (2013). Age. In D. S. K. Thomas, B. D. Phillips, W. E. Lovekamp, & A. Fothergill (Eds.), *Social vulnerability to disasters*, *2nd Ed*. (pp.167-198). Boca Raton, FL: CRC Press.

Pellow, D. (2000). Environmental inequality formation: Toward a theory of environmental injustice. *American Behavioral Scientist*, *43*, 581-601.

Pellow, D. (2017). *What is critical environmental justice?* Cambridge, MA: Polity Press.

Petrie, M. (2006). Environmental justice in the South: An analysis of the determinants and consequences of community involvement in Superfund. *Sociological Spectrum*, *26*, 471-489.

Platt, R. H. (1999). *Disasters and democracy: The politics of extreme natural events*. Washington, DC: Island Press.

Pulido, L. (2015). Geographies of race and ethnicity 1: White supremacy vs white privilege in environmental racism research. *Progress in Human Geography*, *39*, 809-817.

Reid, M. (2010). Gender and race in the history of housing policy and research: From industrialization to Hurricane Katrina. *Sociology Compass*, *4*, 180-192.

Reid, M. (2013). Disasters and social inequalities. *Sociology Compass*, *7*, 984-997.

Rivera, J. D. (2017). Accessing disaster recovery resource information: Reliance on social capital in the aftermath of Hurricane Sandy. In M. Companion & M. Chaiken (Eds.), *Responses to disasters and climate change: Understanding vulnerability and fostering resilience* (pp. 61-70). Boca Raton, FL: CRC Press.

Rubin, C. B. (2009). Long term recovery from disasters—The neglected component of emergency management. *Journal of Homeland Security and Emergency Management*, *6*(1), Article 46. Retrieved from https://journalistsresource.org/wp-content/uploads/2012/10/jhsem.2009.6.1.1616.pdf

Rumbach, A., Makarewicz, C., & Németh, J. (2016). The Importance of place in early disaster recovery: A case study of the 2013 Colorado floods. *Journal of Environmental Planning and Management*, *59*, 2045-2063.

Schlosberg, D. (1999). *Environmental justice and the new pluralism: The challenge of difference for environmentalism*. Oxford, UK: Oxford University Press.

Schlosberg, D. (2009). *Defining environmental justice: Theories, movements, and nature*. New York, NY: Oxford University Press.

Shrader-Frechette, K. (2002). *Environmental justice: Creating equality, reclaiming democracy*. Oxford, UK: Oxford University Press.

Smith, G. (2012). *Planning for post-disaster recovery: A review of the United States disaster assistance framework*. Washington, DC: Island Press.

Thomas, D. S. K., Phillips, B. D., Lovekamp, W. E., & Fothergill, A. (2013). *Social vulnerability to disasters* (2nd ed.). Boca Raton, FL: CRC Press.

Tierney, K. (2006). Social inequality, hazards, and disasters. In D. F. Kettl, R. J. Daniels, & H. Kunreuther (Eds.), *On risk and disaster: Lessons from Hurricane Katrina* (pp. 129-152). Berlin, Germany: De Gruyter.

Tierney, K., Lindell, M. K., & Perry, R. W. (2001). *Facing the unexpected: Disaster preparedness and response in the United States*. Washington, DC: Joseph Henry Press.

Tomes, W. (2011). Impact of the economic downturn on local governments in South Carolina. *Georgia Journal of Public Policy*, *1*(3), 1-11.

Verchick, R. M. (2012). Disaster justice: The geography of human capability. *Duke Environmental Law & Policy Forum*, *23*, 23-71.

Wisner, B., Blaikie, P., Cannon, T., & Davis, I. (2004). *At risk: Natural hazards, people's vulnerability and disasters*. New York, NY: Routledge.

Zanona, M., & Marcos, C. (2017, December 19). House to include $81B disaster aid package in government funding bill. *The Hill*. Retrieved from http://thehill.com/homenews/house/365610-house-to-include-81b-disaster-aid-package-in-government-funding-bill

Zhang, Y., & Peacock, W. G. (2009). Planning for housing recovery? Lessons learned from Hurricane Andrew. *Journal of the American Planning Association*, *76*, 5-24.

Author Biographies

Simone J. Domingue is a doctoral candidate at the University of Colorado Boulder and a graduate research assistant at the Natural Hazards Center. Her research explores how social factors and power inequalities shape institutional responses to hazards and disasters.

Christopher T. Emrich is an Endowed associate professor of Environmental Science and Public Administration at the School of Public Administration and a founding member of the newly formed National Center for Integrated Coastal Research at University of Central Florida (UCF Coastal). His research/practical service includes applying geospatial technologies to emergency management planning and practice, long-term disaster recovery, and the intersection of social vulnerability and community resilience in the face of catastrophe.