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Under-reported and under-served: Disparities in US disaster federal aid-to-damage ratios after hurricanes

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ABSTRACT

The level of outlays that individuals and communities receive following disasters influences the rapidity by and the degree to which they recover. While there is no prescribed formula for the level of aggregate federal aid a county receives, one might expect it to be proportional to the damage sustained. In actuality, the fraction of damages that are covered by disaster aid (which we call "federal disaster coverage") is highly variable. In this work, we investigate the county-level correlates of federal disaster coverage using hurricanes that received Presidential Disaster Declarations from 2008 to 2017 by asking (1) What county and hazard characteristics are important predictors of counties that receive aid but that do not incur damage? and (2) Where damage is reported, what county and hazard characteristics influence federal disaster coverage? We find that counties that receive aid but have no reported damage are more likely to experience greater storm intensity and have more hazard exposure than observations that do not receive aid, suggesting that these counties' damages are unreported. Concerningly, these counties also exhibit greater social vulnerability. Among counties that report damage, we find that federal disaster coverage decreases as hazard intensity and per capita damage increase, suggesting that more severe disasters receive less marginal aid than less severe disasters. Higher local capacity increases the likelihood of aid and the level of coverage. Overall, our findings suggest disparities in how disaster damages are reported in major comprehensive disaster datasets and in how federal aid is disbursed among counties.

Abbreviations

CDBG-DR	Community Development Block Grant Disaster Recovery
FEMA	Federal Emergency Management Agency
HUD	Department of Housing and Urban Development
IHP	Individuals and Households Program

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NFIP	National Flood Insurance Program
NWS	National Weather Service
PA	Public Assistance
PDD	Presidentially-Declared Disaster
RRR	Relative Risk Ratio
SHELDUS	Spatial Hazard Events and Losses Database for the United States
TANF	Temporary Assistance for Needy Families
USACE	United States Army Corps of Engineers

1. Introduction

As the impacts of hazards have risen in the U.S., so have federal disaster recovery and rebuilding expenditures. The five-year average of federal appropriations for disaster relief between 2017 and 2021 was $56 billion, a twelve-fold increase from the five-year average two decades earlier, even when adjusted for inflation [1,2]. Climate change, permissive land-use policies, and economic development are often cited as the main drivers of this escalation in disaster spending, but some scholars have also identified the role that politics, local government capacity, race, and population have in higher outlays per capita and in generating aid inequities [3–7]. The amount of aid that each state, county, and local government receives following a disaster is variable, in part because of heterogeneity in community characteristics, the level of damage sustained, the spatial variability of hazards, and the purpose and structure of various federal aid programs. In particular, the federal approach to funding disaster recovery is fragmented across over 30 federal entities and numerous programs [8]. This fragmentation obscures the level of cumulative federal aid a community receives following a disaster, since different agencies operate their programs with a lack of coordination and there is no prescribed formula for appropriating total federal aid. One might expect it to be relatively proportional to the amount of damage sustained, in part because most recovery programs are primarily based on sustained damage.[1] Nonetheless, it is unclear the extent to which local disaster costs are covered by federal funds and whether such cost redistribution is equitably administered across the nation. Most prior research examines the distribution of federal aid by program and fails to consider the aggregate aid across multiple disaster programs and the overall benefits they deliver to localities.

In this work, we are interested in the fraction of damages that later are covered by federal disaster recovery aid (which we refer to as "federal disaster coverage") and, in capturing the disaster-triggered redistribution of federal funds, how the generosity of federal aid correlates with county characteristics (i.e., the county-level correlates of higher rates of federal disaster coverage and thus lower disaster burden borne by affected localities). We know from the insurance literature that the fraction of damage that is later covered through private insurance is highly predictive of the strength and speed of recovery [9], and, though public funds operate differently than private funds, we might presume that similar recovery patterns would emerge should a study investigate public funds. Yet, a simple investigation demonstrates the federal-aid-to-damage ratio can be highly uneven. For example, when considering the damage reported during Hurricane Harvey in 2017 (Figure A.1a) and the aggregate amounts of federal disaster aid received from the three largest aid programs (i.e., FEMA's Public Assistance Program, FEMA's Individuals and Households Program, and HUD's Community Development Block Grant Disaster Recovery Program, all detailed later) at the county level (Figure A.1b), we find that the fraction of federal coverage ranges from 0.005 to 3,000 - a six-order-of-magnitude difference (Figure A.1c). Many storms produce similar results.

There are multiple possible explanations for the wide range of federal disaster coverages across localities. Some variation is likely tied to how wealth and social vulnerability influence both damage and subsequent aid. For instance, a county with a higher fraction of its population living in poverty might be expected to receive more aid than a wealthier county, all else being equal, because of FEMA's Individuals and Households Program (IHP), a disaster aid program that targets the underinsured and uninsured for financial assistance [10]. Conversely, social vulnerability, such as higher rates of lower-income or minority populations, has been shown to correlate with lower capacity to apply for and access aid due to difficulties in navigating the grant application process [11]. Similarly, poorer regions and communities of color tend to receive less federal assistance to invest in mitigation [12–14]. They also tend to be more exposed to hazards relative to wealthier and whiter communities due to a combination of exclusionary zoning, discrimination in housing, lower housing values, and chronic underinvestment in higher-risk areas [15–18]. All combined, this overexposure may lead to significant damage, but potentially less aid.

A wealthier county, on the other hand, might be expected to receive more aid than a poorer county, because it presumably has more valuable assets and thus have more opportunity for monetary losses [19], and one purpose of federal post-disaster aid is to replace assets people have owned prior to a shock. Amplifying this potential disparity is FEMA's Public Assistance Program (PA), another federal disaster aid program. PA targets public asset and infrastructure recovery and is authorized 5.1-fold more often following disasters than IHP, the aid program targeting the un- and underinsured [20,21]. However, damage and subsequent aid in wealthier areas is often moderated by being comparatively underexposed to hazards, by having received more federal monies for mitigation prior to the disaster, and by having greater access to private insurance products [22]. Thus, we know that wealth and socioeconomic factors can influence damages and aid, but this relationship is complex.

[1] To be declared a disaster, a region must experience more than $4.60 per capita of impact at the county-level and $1.84 per capita impact at the state-level in 2024 [26]. In principle, many disaster programs require that the receiving entities be insured, though many states and local governments "self-insure," making them eligible for aid should a federal disaster be declared and they have a qualifying project [98]. Recent work shows the relationship between damage and aid [4,11].

The variety of purposes, eligibility, availability, accessibility, and program rigidity of federal disaster programs means that the fraction of damages that are covered by federal disaster aid can be highly spatially variable and greater than one (indicating that the amount of aid received is greater than damages reported to have incurred). In this work, we investigate factors that influence federal disaster coverage to understand why some affected areas receive disproportionately more disaster aid based on their damage than others. More specifically, using hurricanes that received Presidential Disaster Declarations from 2008 to 2017, we answer the questions.

(1) What county and hazard characteristics are important predictors of counties that receive aid but that do not incur damage?
(2) Where damage is incurred, what county and hazard characteristics influence federal disaster coverage?

While the factors that influence disaster damage and subsequent federal aid have been explored separately in past research (e.g., Ref. [23]), the factors that influence receipt of federal aid absent damage and that influence federal aid relative to damage have not. Answers to these questions provide important insights into the effectiveness of aid programs for recovery and provide additional context for the unevenness of federal assistance, local disaster burden and their recovery patterns. One million dollars in aid may be substantial if damage is limited, but it is insufficient if damage is orders of magnitude greater. This has serious implications for equity in disaster recovery [24].

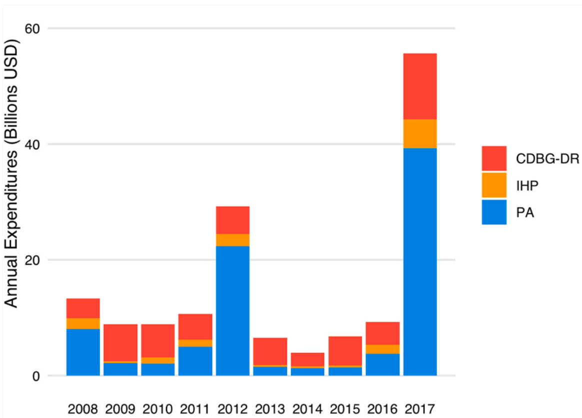
To explore our research questions, we develop multiple regression models over two stages. In the first stage, we answer the first question by building a multinomial logistic regression model to identify the correlates related to a county being in one of four categories following a disaster. The categories are: (1) counties that receive aid, but that do not sustain damage; (2) counties that receive aid and sustain damage; (3) counties that do not receive aid, but that do sustain damage; and (4) finally, counties that neither receive aid nor sustain damage. In the second stage of the analysis, we address the second question. We consider only observations from counties that incur damage, and initially fit a probit model to identify the correlates of receiving zero or greater than zero federal disaster coverage. Then, for observations with a federal disaster coverage greater than zero, we fit a truncated regression model to identify the correlates of lower or higher coverage. The models are built using records from 14 hurricanes that made landfall on the continental U.S. between 2008 and 2017. We limit our analysis to the following programs: FEMA's Public Assistance Program (PA), FEMA's Individuals and Households Program (IHP), and HUD's Community Development Block Grant Disaster Recovery Program (CDBG-DR), because FEMA and HUD provide the majority of the funds for federally-recognized disasters [25]. Mitigation funds are excluded as they are designed to reduce future damage rather than respond to current damage, and federal loan programs (e.g., Small Business Administration disaster loans) are excluded as they must be repaid.

2. Disaster programs, literature, and conceptual model

2.1. Program overview

In the U.S., disasters that surpass a state's ability to adequately respond and recover are designated “Presidentially Declared Disasters” (PDDs) by the President. Affected counties become eligible for emergency management assistance and, often, federal recovery funds. While a state's ability to adequately respond may be highly subjective and spatially variable, PDD eligibility has been standardized primarily based on sustained damages to support program administration. At the time of writing in 2024, FEMA has set a threshold of $1.84 of per capita damage at the state level and $4.60 of per capita damage at the county level to be eligible for a PDD, although some other factors may be taken into consideration [26,27].

The three largest federal disaster recovery programs in terms of outlays are PA, IHP, and CDBG-DR. A county with a PDD may be made eligible for either or both PA and IHP. CDBG-DR funds are allocated to affected states for particularly destructive disasters by Congress. Between 2008 and 2017, more than $153B (2022 USD) were issued through these three programs (see Fig. 1). 81% of these



Year	Most Expensive Event
2008	Hurricane Ike
2009	Southwest and Great Plains Drought
2010	Arizona Severe Weather
2011	Hurricane Irene
2012	Hurricane Sandy
2013	Western Plains Heatwave and Drought
2014	Western Drought
2015	Western Drought
2016	Louisiana Flooding
2017	Hurricane Harvey

Fig. 1. Annual Expenditures for CDBG-DR, IHP, and PA from 2008 to 2017 [20,21,28]. For best viewing, this figure should be printed in color. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

funds in total and 100% of CDBG-DR funds were ad hoc congressional supplemental appropriations, meaning that the funds were unplanned during the annual federal budgeting process [2,20,21,28].

PA is awarded to state and local governments, other public entities, and, on occasion, nonprofits to support the rebuilding of damaged public and municipal infrastructure, including buildings, roads, and bridges. It also reimburses these recipients for disaster-related debris removal and emergency protective services. PA has cost-share requirements for its recipients; recipients are typically reimbursed at a rate of 75% of expenses, though this rate can be higher in particularly distressed areas or following especially severe disasters. There are no project cost caps. PA has been made available in 92% of PDDs since 2000 [21].

IHP is awarded to eligible individuals and households impacted by disasters. Recipients of IHP may receive financial assistance up to $41,000 (in 2023) and other direct services to address immediate household expenses that are un- or underinsured [29]. Direct services are not subtracted from this financial assistance cap. Depending on many factors, IHP could support lodging or rental assistance, home repair assistance, and funeral expenses, among other expenses. The grants are not intended to cover all damages, but rather ensure basic needs are met following a disaster. Indeed, Kousky [30] found that the average IHP grants following Hurricanes Irma and Maria were a mere $2,100 and $3,400, respectively. IHP has been made available in only 18% of PDDs since 2000, meaning it is available far less frequently than PA [20]. IHP does not have cost-share requirements.

HUD's CDBG-DR grants are large grants awarded after particularly devastating disasters (often disasters with more than $2 billion in damages). The grants allow significant flexibility for the initial receiving entity (usually state governments) to determine where and how funds are used, though their spending plan must be approved by HUD. The funds are supposed to prioritize unmet needs in distressed regions, and, while funds are commonly used toward housing (e.g., new housing, property acquisition, rental housing assistance, etc.), the funds can be used toward public and municipal infrastructure or to fund local obligations of PA cost-share.

2.2. Literature and conceptual approach

2.2.1. Factors influencing damage

While damage to physical assets is only one of many ways to measure the severity of a hazard's impact on a community - others include mortality, displacement, job loss, etc. - damage is among the most common metrics in the disaster literature [4,31,32]. It is also the measure that is used by the U.S. federal government to determine whether federal intervention is warranted via a per capita impact threshold to determine PDD eligibility. In the most basic sense, hazard-induced damages are a function of the number of assets that are exposed to the hazard, the value of those assets, the vulnerability of those assets to the hazard, and the intensity of the hazard. More assets, higher-valued assets, less protected assets, more fragile assets (e.g., buildings built to lower code), and stronger hazards all contribute to more damage.

Social, economic, and political factors also influence damage, though indirectly. These factors in an affected community influence the number and value of assets exposed, the extent to which assets are protected from and able to withstand hazard forcing, and even the intensity of hazard forcing an asset is likely to experience. The relationships between these factors, however, are complex and interrelated. For example, when factors that typically moderate hazard risk are excluded, affluent regions are expected to experience more damage and higher losses relative to regions with lower incomes. This is a result of larger and newer homes and, consequently, higher property improvement values [19]. Local governments may also be incentivized to support development in high hazard areas - such as high-demand coastlines - that may attract wealthier tax bases and enrich the local economy but also support some development outside of high-hazard areas, such as low-income housing [33,34]. Affluent regions also benefit from more local, state, and federal investment in public infrastructure, including schools and civic buildings [35]. This combination of more assets and higher-valued assets has the potential to incur greater cost for repair as well as more disaster aid (Howell & Elliot, 2019).

However, affluent communities also have more resources and ability to invest in mitigation, and they tend to benefit from more federal mitigation assistance. First, because of their greater potential for monetary damage, the U.S. Army Corps of Engineers (USACE) builds more protective infrastructure around and FEMA awards more mitigation grants to affluent areas [13,14,36]. This, in part, stems from the benefit-to-cost ratio of these protective investments simply being higher in these areas [37]. Moreover, FEMA mitigation grant cost-share requirements and the USACE requirement that a community pays for asset maintenance mean that many hazard mitigation options are financially out-of-reach for lower-income areas [38].

We draw from existing literature on social vulnerability, which identifies factors that contribute to certain groups being less able to plan for, respond to, and recover from natural disasters [39]. Socially vulnerable communities have endured years of political and social disenfranchisement in the risk management process [40]. In addition to receiving less physical protection from hazards, socially vulnerable communities tend to have infrastructure that is typically older, of lower quality, and built to older engineering standards, and thus more fragile and physically vulnerable to hazards compared to more affluent regions [41]. This is partially a result of a lack of sustained investment in maintenance, but also due to diminished political and social will to invest in these communities [17]. Due to historic discrimination and institutionalized racism, low-income areas are also more likely to have higher percentages of racial minorities and renters, adding an additional layer of marginalization and reduced social, political, and economic capital [42–47].

Finally, social, economic, and political factors influence and reinforce the geographic boundaries of race and class. These boundaries, in turn, influence the groups of people who are exposed to certain hazards. For example, redlining, where the U.S. government refused to back the mortgages of individuals purchasing homes in neighborhoods with racial and religious minorities, led to the partitioning of urban areas into spaces for White homeowners and for racial and religious minorities who rent, along with decades of chronic divestment in red-lined areas [17,42]. The combination of more renters and urban divestment has left these neighborhoods with buildings built to lower standards and also more exposure to hazards. While many argue that socially vulnerable populations today are overexposed to hazards simply as a result of economics (high threat of hazards depreciates land values, making these areas more affordable) [48], exclusionary zoning has been used for more than a century in the U.S., largely in more affluent urban and suburban areas, to ensure neighborhoods maintain their "character" while keeping home values high [49]. Exclusionary zoning ensures these conditions persist.

2.2.2. Factors influencing aid

The level of federal disaster aid that a county receives strongly depends on the level of damage sustained [11]. This is expected as federal disaster determinations and the programmatic design of aid programs are primarily based on damage. However, as with damages, federal disaster aid is also strongly dependent on social, economic, and political factors. While the research in this space is burgeoning, it is common for affluent regions to receive a disproportionate level of disaster aid [5]. This is unsurprising because, as mentioned earlier, these areas are more likely to have the ability to contribute to cost-share requirements (namely for FEMA's PA), and are more likely to have the internal capacity to apply for and subsequently administer grants [9]. There is significant evidence that many wealthier jurisdictions place considerable emphasis on this procurement of federal funds, many with the fiscal resources and staff devoted to this task [50,51]. Local capacity could also include the knowledge built through experience applying for and administering federal grants (i.e., "instrumental learning") [52]. Conversely, low internal capacity is a widely acknowledged barrier for why low-resourced communities continue to receive less federal assistance [53]. To address this, in August 2022, FEMA increased its "small project" maximum for PA from $139,800 to $1 M; small projects have a streamlined application process and fewer reporting requirements, making them, in principle, more accessible to lower-resourced jurisdictions, but the issue of the cost-share has not been formally addressed [26].

Recent studies have found mixed effects of other socioeconomic factors on the receipt of aid. Domingue and Emrich [11] model the influence of a wide range of socioeconomic, demographic, and built environment factors on PA outlays by year and find that aid disparity is tied with specific PDDs that occurred in specific regions.[2] The work demonstrates how inequities can manifest in unique ways and that these inequities may be highly tied with how outlays for specific PDDs are administered in specific regions. For IHP, there is some evidence that the program does not benefit the populations it is designed to serve. Following Hurricane Katrina, lower-income and minority populations received less aid while experiencing more destruction and disruption [54]. This is likely tied to the lack of ease in which potential applicants were able to apply for these funds [55]. More recently, several trends pertaining to the challenges that communities of color have in obtaining IHP assistance, housing repair and replacement assistance, and other needs assistance, have been found to persist [5].

Additional social and political factors have also been found to influence outlays. For instance, Eisensee and Strömberg [56] find that increased media coverage, which likely places more pressure on federal administrators to effectively respond to a crisis, influences federal disaster decisions. Conversely, they find that media coverage on disasters can be crowded out by other newsworthy material, and that subsequent relief decisions are impacted. Further, federal disaster aid has been leveraged to gain political advantage. Electorally-competitive states have been found to be more likely to receive a PDD and receive federal disaster assistance following a disaster than less electorally-competitive states, and PDDs are more likely to be declared during election years [6,57]. Federal disaster expenditures in states with congressional representation on FEMA oversight committees are also found to have greater disaster expenditures [58]. Finally, political ideology and leanings within communities may influence local receptiveness to federal assistance and preferences over which level of authority should oversee risk management and disaster recovery [59]. More conservative areas report preferring self- or locally-derived risk management strategies, with lack of trust in government being cited as a main driver for this preference. Further, conservative-leaning individuals are less likely to report that they believe federal assistance will be made available to them following a disaster, which, in turn, can influence how they prepare for hazards [60].

2.2.3. Factors influencing federal disaster coverage (conceptual model)

Our two primary research questions aim to identify county and hazard characteristics of counties that receive aid but report no damage (Stage 1) and factors that influence the degree of county-level federal disaster coverage (Stage 2).[3] These questions are investigated separately to absolve issues related to having a zero in the denominator for federal disaster coverage (i.e., aid divided by damage). While, as we have outlined, existing literature has investigated hazard, social, economic, and political factors that contribute to disaster damage and federal disaster aid separately, we explicitly explore how these factors influence the fraction of losses that the federal government covers (Fig. 2). While it is clear that federal aid generally increases as damages increase [11], it is unclear whether this relationship has increasing, decreasing, or constant returns-to-scale. More specifically, it is not clear whether these rates match on the margins.

As illustrated in our conceptual framework (Fig. 2), we posit that federal disaster coverage will be influenced by a complex combination of hazard intensity, asset exposure, damages, and social, economic, and political factors. In terms of hazard intensity, it is well established that more powerful storms lead to greater outlays *ceteris paribus* [61]. Areas that experience greater storm intensity - such as those that are subjected to higher wind speeds, increased precipitation, deeper flooding depths, and larger storms - sustain greater damages [61–66]. However, as storm intensity increases, the rates at which damage and aid increase relative to each other are unknown (Fig. 2, Arrow 1). With increased storm intensity, if damage were to increase at a greater rate than aid, federal disaster coverage would decrease. Conversely, with increased storm intensity, if aid were to increase at a greater rate than damage, federal disaster coverage would increase.

[2] While they found many factors that extend beyond damage are significant, suggesting that some level of procedural (or process) inequities exist, relevant factors vary significantly among years. For example, while a lower fraction of the population who are renters or who live in mobile homes is associated with significantly more PA per capita, this is found to be true only in 2015; in 2013, lower per capita income is associated with significantly more PA per capita.

[3] Stage 2 includes observations with a federal disaster coverage of zero, meaning a county that received no aid yet sustained damage.

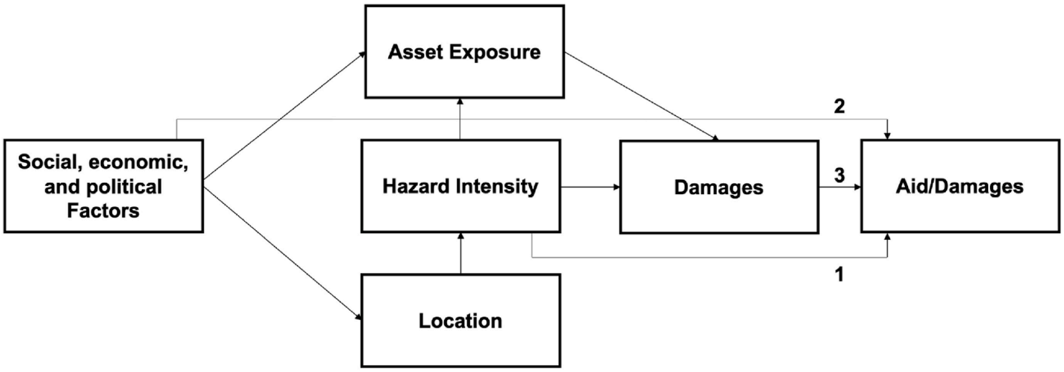


Fig. 2. Conceptual model of influencing factors of federal disaster coverage.

We similarly anticipate that the effects of social, political, and economic factors on federal coverage will be mixed (Fig. 2, Arrow 2). Regardless of hazard intensity, wealthier and whiter counties and counties with higher capacity will be more effective at navigating the processes to receive federal aid [9]. At the same time, areas with lower capacity and higher rates of socially vulnerable populations are often underserved by disaster assistance. The reasons for this include difficulty navigating the aid application process, program ineligibility (e.g., programs exclusive to homeowners), reduced fiscal capacity to meet cost-share requirements, and reduced motivation of local, state, and federal officials to serve communities with weaker political strength [3,4,54,55,61]. For these reasons, we therefore expect federal disaster coverage to be lower for counties with less capacity and more socially vulnerable populations, assuming damage is held constant. However, we know the relationship between social vulnerability, local capacity, and damage is complex, as previously discussed. Thus, even though increased social vulnerability and reduced local capacity decrease the likelihood of receiving federal aid, its impacts on damage are ambiguous.

Finally, as asset exposure increases - due to less mitigation, more assets, or higher-valued assets in total, damage is expected to increase, along with aid (Fig. 2, Arrow 3). Disaster aid programs are primarily predicated on damage. However, the rate at which aid increases as damage increases is unclear.

3. Data

This research focuses on federal disaster coverage for 14 hurricanes that made landfall in the Southeast and Mid-Atlantic U.S. between 2008 and 2017. This represents 61 PDDs, as each state affected by a disaster receives its own PDD (i.e., one hurricane can result in multiple PDDs). The geographic unit of analysis is the county level and the temporal unit of analysis is the year of the PDD. Any county included in any of the 61 PDDs is included in our analysis, even if they did not sustain damage nor receive aid. FEMA data for IHP and PA are collected from FEMA's Open Source database [20,21], and then are aggregated to the county level. Note that some PA projects are issued to state agencies, so it is not obvious where these funds are ultimately distributed. These records are excluded from our analysis. Furthermore, there is a possibility for mutual aid to occur where one entity effectively “donates” goods or services and then seeks reimbursement for this donation through PA. Out of the 112,510 PA projects in the dataset representing hurricane PDDs between 2008 and 2017, mutual aid is known to have occurred 1,212 times based upon project titles. These projects were excluded when aggregating PA awarded at the county level.

CDBG-DR data are scraped from portable document files (PDFs) of CDBG-DR action plans. A CDBG-DR action plan exists for each funded project and reports, among a host of categories, the CDBG-DR contribution toward the project, and the county(ies) in which the receiving entity (e.g., non-profit, local government) is located. Some CDBG-DR projects are awarded to state agencies and there is no ability to track in which county the funds were spent via the action plan. These records were excluded from our analysis. After the data are scraped, we aggregate the CDBG-DR contribution to the county-level for each hurricane. It is possible that the project or the receiving entity spans multiple counties. In these instances, having no better information, we divide project funding evenly among the listed counties. Also, CDBG-DR action plans were not available for Hurricane Irma funds for Florida, Hurricane Irene funds for New Jersey, and Hurricane Sandy funds for New Jersey. Additionally, project spending plans were not available for 1.1% of CDBG-DR funds designated for Texas following Hurricane Harvey. In these instances, we assumed that the CDBG-DR funds that were allocated by Congress for that state are distributed evenly among the eligible counties (i.e., counties included within the state PDD). Because the CDBG-DR grant data are approximate due this missing data, as a robustness check, we model federal disaster coverage both with and without CDBG-DR data included (see Tables A.1 and A.2 in the Appendix). There is little appreciable difference in the results.

Counties included within a PDD but that do not receive aid are assigned $0 in aid. We highlight the fact that disaster aid from all three programs are aggregated at the county-level, despite all three programs operating under different rules and purposes. Our rationale is that there are many different federal programs administering disaster relief aid to state and local governments as well as affected individuals, households, and businesses. Given the diversity and fragmentation of these programs [8], there is a nebulous upper limit of federal relief funding a locality can receive in total after experiencing a disaster. It is possible that a county with more resources and strong administrative capacity may acquire significantly more federal funds in aggregate from various programs which are disproportionate to its sustained damage. We also aggregate outlays because CDBG-DR funds are for unmet needs, usually in excess of what FEMA, other federal programs, and insurers cover. For example, if entities in a county received an unusually high amount of PA, we would expect them to receive less HUD funding. (We note that this comment reflects programmatic design and not an empirical investigation.) For these reasons, aid is aggregated, though results using only PA aid at the county-level as the response variable are presented in the Appendix (Tables A.3 and A.4). The final dataset consists of 1,943 county-PDD observations.

We collect *damage* data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), a hazard loss dataset maintained by the Arizona State University Center for Emergency Management and Homeland Security [67]. From this dataset, we collected *property damages* and *fatalities* for each county-PDD pairing. We do not include crop damages because these losses are frequently restituted by other federal aid and insurance programs, such as the US Department of Agriculture's Emergency Conservation Program or the USDA's Federal Crop Insurance Program. SHELDUS data are imperfect. First, the bulk of SHELDUS records are derived from the National Weather Service (NWS) Storm Events Database [68], which means local stations must record an event for it to be flagged in the SHELDUS database. The spatial scale used by this database is a mix of counties and NWS Public Zones. When an NWS zone is used, and when this zone intersects multiple counties, SHELDUS must evenly distribute losses among these counties. Further, past research has found that SHELDUS tends to underestimate losses [69]. Counties included within a PDD but with no reported damage are assigned $0 in damage. All damage and aid data are Consumer Price Index (CPI) adjusted to 2019 dollars.

Table 1 provides a list of the variables used in the modeling process along with their summary statistics. Independent variable selection is informed by our conceptual models and literature on the determinants of disaster damage and disaster aid. We performed a multicollinearity analysis for all independent variables, ensuring that all variance inflation factors were less than five [70]. Hurricane intensity data is primarily collected using Anderson et al.'s [71,72] open-source R packages *'hurricaneexposure'* and *'hurricaneexposuredata.'* For each county-PDD pair, we collect the maximum 10-m 1-min *sustained wind speed* at the county's population centroid. The package leverages the Willoughby hurricane wind speed model to interpolate these figures [73,74]. Also from this package, we collect the minimum *distance between the storm track and the population centroid* for each county. *Precipitation* data, specifically cumulative rainfall starting two days prior and ending on the day the storm dissipated, is

Table 1
Summary statistics of variables used in Stage 1 and 2 models.

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Disaster variables					
Federal disaster coverage	1100	27.74	288.06	0	7552.15
Fatalities (persons)	1943	0.30	2.39	0	72.00
Precipitation (inches)	1943	5.26	4.56	0	49.31
Property damage (2019 USD)	1943	1.12e+8	1.25e+9	0	2.65e+10
Property damage per capita (2019 USD)	1943	623.77	4228.27	0	8.27e+4
Storm distance (kilometers)	1943	199.46	161.21	0.14	1164.61
Total aid (2019 USD)	1943	2.46e+7	3.97e+8	0	1.70e+10
Wind velocity (meters per second)	1943	15.17	7.77	0.53	53.07
County variables					
Coastal (binary)*	1943	0.24	0.42	0	1.00
FEMA Region 1 (binary)*	1943	0.05	0.22	0	1.00
FEMA Region 2 (binary)*	1943	0.07	0.26	0	1.00
FEMA Region 3 (binary)*	1943	0.20	0.40	0	1.00
FEMA Region 4 (binary)*	1943	0.45	0.50	0	1.00
FEMA Region 6 (binary)*	1943	0.23	0.42	0	1.00
Land area (square miles)*	1943	616.77	351.26	2	3361.48
Median house age (years)	1943	34.12	9.59	12	73.00
Median household income, log (2019 USD)	1943	10.81	0.28	10.01	11.80
Number of previous PDDs with aid	1943	4.14	3.06	0	17.00
Percentage of Democrat votes (%)	1943	41.93	16.21	8.43	92.46
Percentage of land in floodplain (%)*	1943	22.61	21.14	0	100.00
Percentage of mobile homes (%)	1943	16.39	11.24	0	57.99
Percentage of racial minorities (%)	1943	27.55	18.34	0.18	86.27
Percentage of renters (%)	1943	29.14	9.05	10.01	80.89
Percentage of population 65+ (%)	1943	16.27	4.43	3.20	56.71
Percentage receiving PA (%) (e.g., TANF)	1943	2.15	1.26	0	13.72
Swing county (binary)	1943	0.09	0.28	0	1.00
Tax revenue per capita (thousands 2019 USD)	1943	1.40	1.81	0	37.16
Total population, log	1943	10.87	1.38	5.48	15.35
Unemployment rate (%)	1943	8.28	3.14	0	24.70
Urban (binary)*	1943	0.53	0.50	0	1.00
Year 2008 (binary)	1943	0.21	0.41	0	1.00
Year 2009/2010 (binary)	1943	0.04	0.20	0	1.00
Year 2011 (binary)	1943	0.12	0.33	0	1.00
Year 2012 (binary)	1943	0.27	0.44	0	1.00
Year 2016 (binary)	1943	0.11	0.31	0	1.00
Year 2017 (binary)	1943	0.25	0.43	0	1.00

Note: Variables with * are time-invariant by county.

collected at the county level using the Applied Climate Information System data-querying tool xmACIS2 developed by the National Oceanic and Atmospheric Administration Northeast Regional Climate Center [75].

To control for a county's baseline time-invariant hazard risk, we include the *percentage of the county's area within FEMA's Special Flood Hazard Area* [76]. The Special Flood Hazard Area are areas mapped by FEMA, ultimately for flood insurance purposes, and are deemed to have a 1% or greater probability of being flooded in a given year. This time-invariant metric proxies county flood risk. We also include a binary indicator for whether the county is *coastal*, which has been found to be a significant factor in determining public disaster assistance allocation [23]. Finally, we include the *total land area of a county* to control for its size [77].

We include three variables to capture the local administrative capacity of a county. FEMA divides the U.S. into ten *administrative regions*. Schmidtlein et al. [78] demonstrate how these administrative regions are important for determining the outlays, likely due to differences in how policies and rules are administered. The PDDs under consideration in this work span six FEMA regions, and thus we constructed time-invariant binary variables to indicate to which FEMA region a county belongs. As there are only two county-PDD observations in FEMA Region 5, these observations and, consequently, this FEMA region, are omitted from the analysis to prevent singularity issues when fitting the model, resulting in five total time-invariant binary variables [79]. Figure A.2 provides a map of these FEMA regions. We also construct a variable for each county-PDD pairing that is a count of the *number of PDDs for which the county received* PA funds between 1995 and the PDD of interest. PDD-county pairings in which the county received only IHP and/or CDBG-DR were excluded from this count, as IHP is granted to individuals and CDBG-DR is first issued to the state. Only 85 PDD-county pairings received IHP or CDBG-DR but not PA. The rationale is that a county with more PDDs with aid prior to a disaster are expected to have more experience applying for and subsequently administering grants. Finally, we collect each county's per capita *own-source tax revenue* in the year prior to the PDD [80].

We capture the condition of the built environment using four indicators. These indicators include the *percentage of houses that are mobile (or manufactured) homes*, the *median age of county homes*, and *the percentage of the population who are renters* [81]. To indicate whether the county is *rural or urban*, we use the U.S. Department of Agriculture 2013 Rural-urban Continuum Codes [82]. Counties with metropolitan codes (i.e., codes 1–3) are assigned a binary variable indicating their urban status, and the remaining counties are designated as rural. County-level socioeconomic and demographic characteristics are measured using *total county population* (logged), the *percentage of the population that is nonwhite*, the *percentage of the population that is 65 years of age and older*, *median household income* (logged), the *percentage of households receiving public assistance through at least one social welfare program* (e.g., Temporary Assistance for Needy Families (TANF)), and *the unemployment rate of the county* [81]. These data are collected from the 5-year American Community Survey, and we use the five-year range in which the year of the PDD is the middle value. These socioeconomic and demographic characteristics were selected to account for important, known dimensions of social vulnerability, especially race, age, and income [39]; [41,83].

To capture the political influence on these processes, we include two political indicators that correspond to the presidential election most recent to the PDD: the *percentage of the county's population that voted for the Democratic presidential candidate* and whether the *county was a swing county* [84]. A swing county is defined as one in which the difference between the percentage of the county that voted for a Democratic candidate and the percentage of the county that voted for a Republican candidate was less than or equal to five percent. The idea of this variable is to capture counties that are potentially more politically-important to elected officials [58].

Finally, we include *year* dummies to account for yearly national shocks. There are only two PDD-county observations for 2009, which causes convergence problems during parameter estimation. To address this, we combine year dummies for 2009 and 2010.

4. Methodology

4.1. Stage 1

In the first stage, we answer the question "What county and hazard characteristics are important predictors of counties that receive aid but that do not incur damage?" We do this by examining the correlates related to a county being in one of four categories: (1) counties that receive aid, but that do not sustain damage (*No Damage, Aid*) (i.e., the category in question, which also later becomes the reference category); (2) counties that receive aid and sustain damage (*Damage, Aid*); (3) counties that do not receive aid, but that do sustain damage (*Damage, No Aid*); and (4) finally, counties that neither receive aid nor sustain damage (*No Damage, No Aid)*. Fig. 3a is a scatterplot of total damage versus total aid for all county-PDD observations divided into the four categories. Of the 1,943 county-PDDs observations, 422 are *No Damage, Aid* observations in which the county reported no damage yet still received aid, ranging from $1,021 to $1.03B (CPI adjusted to 2019 dollars). We use this category as our omitted "reference category" to which the other three categories are compared. The rationale is that this combination of not sustaining damage while still receiving aid is unexpected as it runs counter to the intentions of federal aid programs. There are 193 county-PDDs that received no aid, but that sustain damage ranging from $208 to $4.15 M (CPI adjusted to 2019 dollars). This is also an unexpected outcome (the federal coverage ratio here is 0), and is investigated further in Stage 2.

Fig. 3b shows the spatial distribution of the categories from Fig. 3a. For counties with more than one observation, the mode over all categories is shown. Interestingly, observations that received aid but that sustain no damage (most often) are mainly clustered along the Eastern coastline. Additional data discovery related to the four categories in Stage 1, including the density of observations in the categories *No Damage, Aid* and *Damage, No Aid* (Figure A.3) and boxplots of select variables by category (Figure A.4) is in the Appendix.

To address the research question, we fit the categorical data using a multinomial logistic regression model (Eq. (1)). By using a multinomial logistic regression model, we are able to treat observations as discrete categories and examine the systematic differences among them falling under different categories. The dependent variables are county-PDD observations that have been binned into the

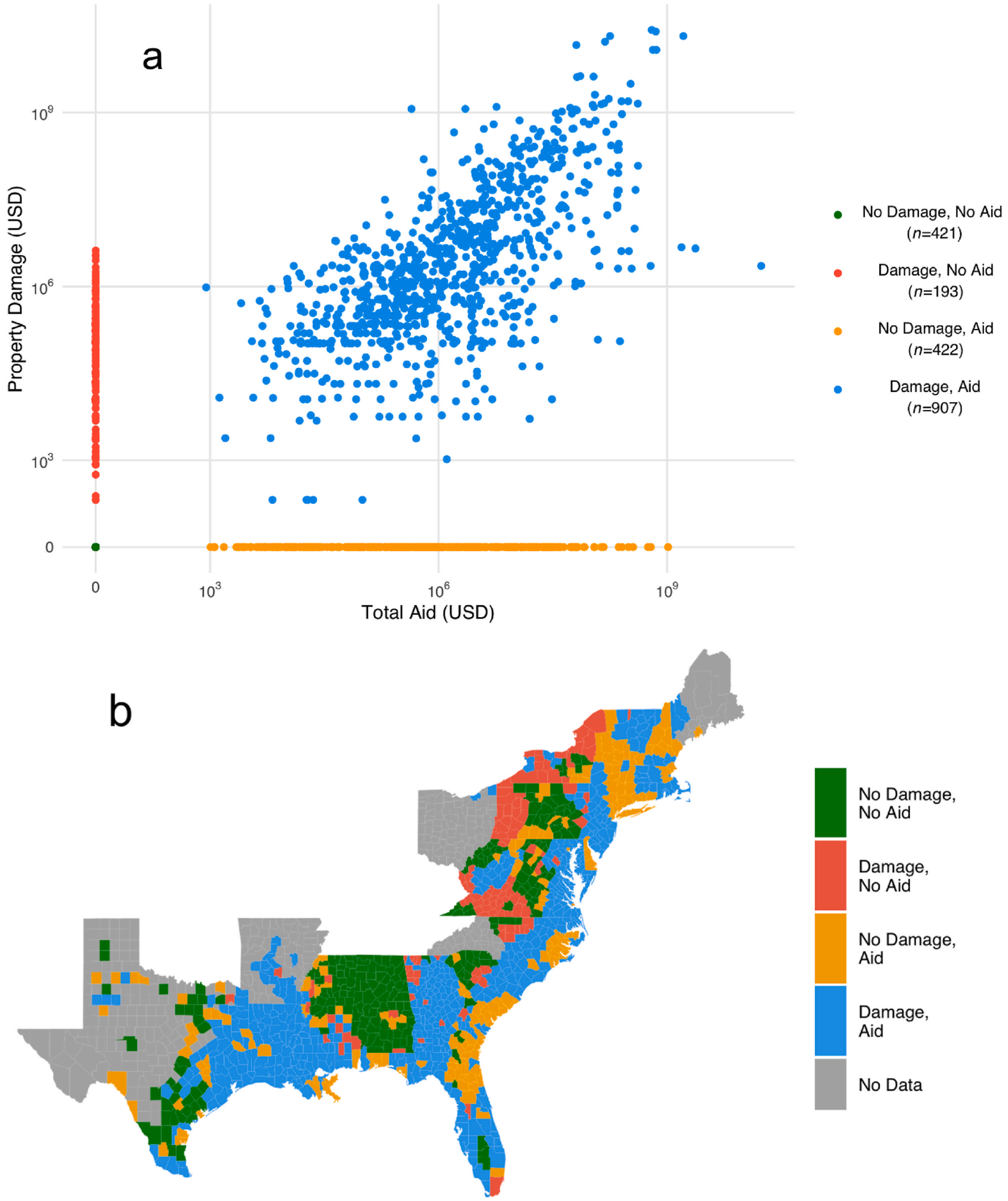


Fig. 3. a. A scatterplot of sustained damage versus total aid for each county-PDD observation; **b.** The spatial distribution of the scatterplot. For counties with more than one observation, the mode is reported. For best viewing, this figure should be printed in color. The base map in Fig. 3b is from 2022 TIGER/Line Shapefiles, prepared by the U.S. Census Bureau. It is in the public domain and is not copyrighted [85]. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

four categories, Y_{cp}, for county c and PDD p. The reference category, $Y_{cp} = k_0$, is the *No Damage, Aid* category - i.e., the category that runs counter to the intent of disaster aid. Using maximum likelihood estimation, the model estimates parameters that maximize the multinomial log-odds, $ln\left(\frac{P(X_i)}{P(X_0)}\right)$, for the dependent variable's three alternative categories, $Y_{cp} = k_i$, $i = 1,2,3$. The model is a linear function of county-level time-variant hazard variables, H_{cp}; county-level time-invariant risk variables, F_c; county-level time-invariant urbanization variable, U_c; and county-level time-variant socioeconomic, demographic, infrastructure, and political variables, D_{ct_p}, for county c in year t, the year in which PDD p occurred. Model error is represented by ε_{cp}.

$$ln\left(\frac{P\left(Y_{cp}=k_i\right)}{P\left(Y_{cp}=k_0\right)}\right)=\alpha+\beta H_{cp}+\gamma F_c+\delta D_{ct_p}+\zeta U_c+\varepsilon_{cp} \tag{1}$$

The model is estimated using the '*mlogit*' package in R [86]. Model coefficients are exponentiated to produce the variables' relative risk ratios (RRR), which indicates the variable's marginal impact on the likelihood of the dependent variable, *ceteris paribus*. An RRR greater than 1 indicates that a unit increase in the independent variable increases the probability of the dependent variable's category.

4.2. Stage 2

In the second stage of our analysis, we find the correlates related to receiving higher or lower federal disaster coverage in counties that sustained damage. That is, observations with no reported damage are omitted. Fig. 4a shows the distribution of federal disaster coverage. Because of its heavy skew, Fig. 4b shows this same distribution, except with federal disaster coverage logged. The majority

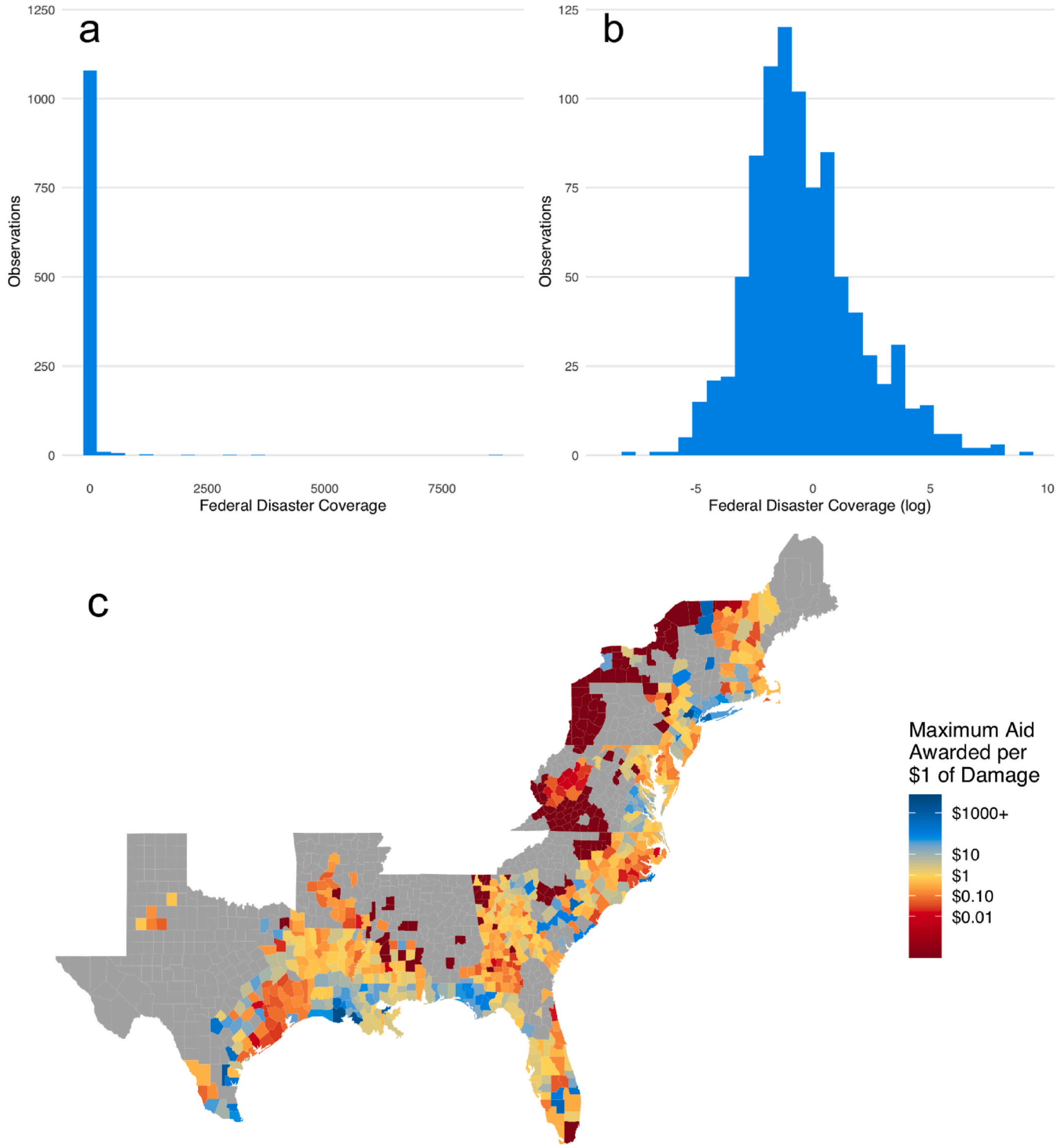


Fig. 4. a. Histogram of the distribution of federal disaster coverage for observations with sustained damage; **b.** Histogram of the distribution of federal disaster coverage, logged, for observations with sustained damage. Note that observations with federal disaster coverage of zero ($n = 193$) are undefined when logged and omitted; **c.** The spatial distribution of the observations in the histogram. For counties with more than one observation, the highest federal disaster coverage over all PDDs is shown. For best viewing, this figure should be printed in color. The base map in Fig. 4c is from 2022 TIGER/Line Shapefiles, prepared by the U.S. Census Bureau. It is in the public domain and is not copyrighted [85]. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

of observations (71%) are less than or equal to one, and 62% have a federal disaster coverage less than 0.5. Ten percent (10%) of observations have a federal disaster coverage value greater than 10, meaning they received at least 10 times more aid than reported damage. Fig. 4c displays the spatial distribution of federal disaster coverage. For counties with more than one observation (i.e., counties with more than one PDD), the highest federal disaster coverage over all PDDs is displayed. Again, spatial clustering is present, with inland areas receiving less federal disaster coverage and counties closest to the coastline receiving higher federal disaster coverage.

To determine the correlates of higher and lower levels of federal disaster coverage, we fit all nonzero damage data using a two-tier model [87]. Zero damage leads to an undefined federal coverage ratio, so these observations are excluded from this analysis. The federal disaster coverage can take on only a zero value or a positive value, meaning that the dependent variable is limited by a corner solution at zero and a two-tier model is required. The first tier uses a probit model (Eq. (2)) to estimate the probability of a positive federal disaster coverage. The response variable of the probit model is the probability that the binary latent variable Y_{cp} (for county c and PDD p) is equal to 1. Y_{cp} takes the value of $Y_{cp} = 0$ when the county-PDD federal disaster coverage value (y_{cp}) is equal to 0, and $Y_{cp} = 1$ when $y_{cp} > 0$ (Eq. (3)). The second tier uses a truncated normal regression model (Eq. (4)) to predict the outcomes of all positive federal disaster coverage observations. The dependent variable is the inverse hyperbolic sine of the percentage value of the variable y^*_{cp}, the nonzero county-PDD federal disaster coverage values, $y_{cp} > 0$ (Eq. (5)). The transformation controls for the skew of federal disaster coverage observations. Both models are linear functions of county-level, time-variant hazard variables, H_{cp}; county-level time-invariant risk variables, F_c; county-level time-invariant urbanization variable, U_c; and county-level time-variant socioeconomic, demographic, infrastructure, and political variables, D_{ct_p}, for county c in year t, the year in which PDD p occurred. Model error is represented by ε_{cp}.

$$P\left(H_{cp}, F_c, D_{ct_p}, U_c\right) = \Phi\left(\alpha + \beta H_{cp} + \gamma F_c + \delta D_{ct_p} + \zeta U_c\right) \tag{2}$$

$$Y_{cp} = \begin{cases} 1, & y_{cp} > 0 \\ 0, & y_{cp} = 0 \end{cases} \tag{3}$$

$$asinh\left(y^*_{cp}\right) = \alpha + \beta H_{cp} + \gamma F_c + \delta D_{ct_p} + \zeta U_c + \varepsilon_{cp} \tag{4}$$

$$y^*_{cp} = y_{cp} \middle| y_{cp} > 0 \tag{5}$$

The probit model is estimated using the 'stats' package in R [88], and the truncated normal regression model is estimated using the 'truncreg' package in R [89]. Estimates in both tiers are obtained using maximum likelihood estimation.

5. Results and Interpretation

5.1. Stage 1

The RRRs, standard errors, and statistical significance of the multinomial logistic regression model for Stage 1 of our approach are shown in Table 2. The reference category is *No Damage, Aid* for the aforementioned reasons. This allows us to compare this category to all alternate categories simultaneously. Specifically, we assess the marginal impact of the independent variables on the likelihood of being in an alternate category relative to the omitted reference category.

The model has several statistically significant hazard intensity indicators. First, we find that, as precipitation increases by 1 inch, an observation is 0.698 times as likely (i.e., less likely) to be categorized in the *No Damage, No Aid* category, and 1.148 times as likely (i.e., more likely) to be categorized in the *Damage, Aid* category relative to the reference category, *No Damage, Aid*. As wind speed increases, an observation is 0.870 and 0.824 times as likely (i.e., less likely) to be in the categories *No Damage, No Aid* and *Damage, No Aid*, respectively, and 1.036 times as likely (i.e., more likely) to be in the category *Damage, Aid* relative to our reference category *No Damage, Aid*. Finally, as the minimum distance between county geo-centroid and the hurricane eye increases by 1 km, an observation is 0.998 times as likely (i.e., less likely) to be in the categories *No Damage, No Aid*, though this finding is weakly significant.

These results suggest greater storm intensity, as measured by precipitation and wind velocity, increases the likelihood of falling into the *Damage, Aid* category, relative to the *No Damage, Aid* category. This is expected as greater storm intensity is likely to lead to damage. Second, greater storm intensity, as measured by wind velocity in particular, reduces the likelihood of falling into the *No Damage, No Aid* and *Damage, No Aid* categories, relative to the *No Damage, Aid* category. The former suggests that as storm intensity increases, recipients are more likely to receive aid even when no damage is sustained. The latter, surprisingly, suggests that as storm intensity increases, a county is more likely to sustain no damage and receive aid than to sustain damage and receive no aid. On one hand, we would expect greater hazard intensity to result in greater aid [61]; on the other hand, we would not expect greater hazard intensity to result in less damage [62,65].

Variables representing hazard exposure - namely the coastal county indicator and the percentage of land in the floodplain - are also statistically significant in our model. Specifically, observations that are coastal counties are less likely (0.370 times as likely) to be categorized in the *No Damage, No Aid* category than our reference category of *No Damage, Aid*. That is, coastal counties are far more likely to sustain no damage and receive aid than to sustain no damage and receive no aid. Similarly, with every 1% increase in county land within the floodplain, observations are 0.987 times as likely (i.e., less likely) to be categorized in the *Damage, Aid* category than the reference category, *No Damage, Aid*. Despite the weak effect, this finding, also counterintuitive, indicates that observa-

Table 2
Results of Stage 1 multinomial logistic regression for predicting damage and aid classification. The baseline category is *No Damage, Aid*. This allows us to compare this category to all alternate categories simultaneously. Parameters are reported as RRRs.[4,5].

	No Damage, No Aid n = 421	*Damage, No Aid n = 193*	*Damage, Aid n = 907*
Intercept	1.7e+04 (9.019)	65.24 (11.02)	1.9e+06 (6.687) *
Disaster variables			
Fatalities (persons)	0.501 (0.602)	0.464 (0.568)	1.089 (0.050)
Precipitation (inches)	0.698 (0.041) ***	0.953 (0.045)	1.148 (0.022) ***
Storm distance (kilometers)	0.998 (8.6e-04) *	0.998 (1.2e-03)	1.000 (7.3e-04)
Wind velocity (meters per second)	0.870 (0.027) ***	0.824 (0.034) ***	1.036 (0.015) *
County variables			
Coastal (binary)	0.370 (0.345) **	0.716 (0.367)	1.069 (0.180)
FEMA Region 2 (binary)[5]	3.596 (0.932)	3.117 (0.707)	0.219 (0.373) ***
FEMA Region 3 (binary)[5]	91.04 (0.884) ***	31.78 (0.723) ***	0.774 (0.394)
FEMA Region 4 (binary)[5]	34.52 (1.014) ***	30.29 (0.938) ***	1.370 (0.532)
FEMA Region 6 (binary)[5]	10.01 (1.003) *	9.009 (0.980) *	1.006 (0.520)
Land area (square miles)	1.000 (3.1e-04)	0.999 (4.2e-04) **	0.999 (2.3e-04) ***
Median house age (years)	1.026 (0.016)	1.049 (0.017) **	0.985 (0.011)
Median household income, log (2019 USD)	0.638 (0.759)	0.660 (0.923)	0.338 (0.575)
Number of previous PDDs with aid	0.795 (0.045) ***	0.862 (0.050) **	1.161 (0.028) ***
Percentage of Democrat votes (%)	1.039 (0.011) ***	1.048 (0.014) ***	1.017 (8.5e-03) *
Percentage of land in a floodplain (%)	0.993 (6.2e-03)	1.002 (7.9e-03)	0.987 (3.8e-03) ***
Percentage of mobile homes (%)	0.980 (0.015)	0.981 (0.019)	0.980 (0.010)
Percentage of racial minorities (%)	0.973 (9.8e-03) **	0.967 (0.012) **	1.001 (7.6e-03)
Percentage of renters (%)	0.950 (0.016) **	0.946 (0.020) **	0.956 (0.012) ***
Percentage of population 65+ (%)	0.943 (0.031)	0.983 (0.034)	0.993 (0.020)
Percentage receiving PA (%) (e.g., TANF)	0.981 (0.081)	1.123 (0.094)	0.929 (0.061)
Swing county (binary)	1.018 (0.323)	0.699 (0.385)	1.062 (0.235)
Tax revenue per capita (thousands 2019 USD)	1.096 (0.062)	0.699 (0.161) *	1.023 (0.044)
Total population, log	0.803 (0.118)	1.122 (0.145)	0.967 (0.085)
Unemployment rate (%)	1.009 (0.040)	0.896 (0.055) *	0.946 (0.032)
Urban (binary)	1.090 (0.233)	1.192 (0.281)	1.077 (0.182)
Year 2009/2010	0.228 (0.418) ***	0.146 (0.837) *	0.201 (0.368) ***
Year 2011 (binary)	0.017 (0.904) ***	0.045 (1.163) **	0.647 (0.347)
Year 2012 (binary)	1.154 (0.452)	7.276 (0.521) ***	0.864 (0.293)
Year 2016 (binary)	2.656 (0.464) *	2.672 (0.599)	0.176 (0.334) ***
Year 2017 (binary)	0.335 (0.382) **	0.318 (0.548) *	0.514 (0.279) *
P-value of model	***1.58e-275***		

*p < 0.5, **p < 0.01, ***p < 0.001

tions in the *No Damage, Aid* category are more exposed to flooding, and supplements the previous finding that observations in the *No Damage, Aid* category also experience more severe storm conditions (as measured by wind velocity, in particular) than counties that do not receive aid. One possible explanation is that counties in the *No Damage, Aid* category are aware that they are more exposed to hazards and have taken steps to reduce their vulnerability, though the aid is still dispersed because of their high exposure. This is plausible given that under Section 406 of the Stafford Act (the law that dictates most federal disaster response), PA can be used for mitigation and not recovery. A related explanation is that these counties are simply receiving aid despite their post-hazard condition and past actions. Anecdotally, this was seen in Coryell County, TX which received millions of dollars in CDBG-DR funding following Hurricane Harvey in 2017 despite sustaining no damage in the county [24]. Another plausible explanation is that, in reality, the counties are experiencing storm damage and receiving aid for that damage, but the damage is unreported by SHELDUS. For instance, Chatham County, GA sustained over $30 million in damage following Hurricane Matthew in 2016, as reported by the *Savannah Morning News,* yet had no reported damage in the SHELDUS dataset [67,90]. When we investigate IHP data with more depth, of the 422 county-PDD observations in the *No Damage, Aid* category, 106 observations were from counties that received IHP. Part of the IHP reporting includes residential damage of IHP recipients. The reported cumulative county-level residential damage across these 106 observations ranges from roughly $40K to $233 M (standard deviation of $26.1 M). Ultimately, if a lack of reporting of damage is in fact occurring, the observations in the *No Damage, Aid* category potentially have actual cumulative damages less than those in the *Damage, Aid* category. We conclude this because observations in the *No Damage, Aid* category experience, on average, lower storm intensity than observations that receive aid and incur damage (see Figure A.4). Lower levels of damage may be a potential driver for this reporting error, but this should be investigated further.

Regarding the social vulnerability and capacity variables, we find that the percentage of renters has significant RRRs across all three alternative categories: *No Damage, No Aid; Damage, No Aid;* and *Damage, Aid*. The percentage of racial minorities and unemployment rate also have significant RRRs for the *Damage, No Aid* category and the percentage of racial minorities is also significant for the

[4] Results with CDBG-DR outlays omitted are presented in Table A.1. The results are highly similar to our baseline estimates.

[5] The baseline FEMA region in the model is FEMA Region 1. The states within each FEMA region are: FEMA Region 1 (CT, MA, ME, NH, RI, VT); FEMA Region 2 (NJ, NY); FEMA Region 3 (DC, DE, MD, PA, VA, WV); FEMA Region 4 (AL, FL, GA, MS, NC, SC); FEMA Region 6 (AR, LA, TX).

No Damage, No Aid category. Interestingly, all of these variables have RRRs less than 1, indicating that as the region becomes more socially-vulnerable as measured by more renters, more racial minorities, and greater unemployments rates, there is a decreased likelihood of being categorized in the alternative categories relative to our reference category of *No Damage, Aid*. In other words, as social vulnerability increases, a county is more likely to be in the reference category, *No Damage, Aid*. This is another surprising result. Areas with higher social vulnerability are often disproportionately exposed to disaster damage and have fewer internal resources to recover. We would expect, therefore, these locations to receive aid but also sustain significant damage. If this is the case, and damage is incurred in these areas, this provides evidence of underreporting damage in loss datasets. Gallagher [91] documented this underreporting issue, demonstrating a pervasive non-random missing data problem in SHELDUS. Disaster loss datasets are used to guide research and subsequent disaster recovery policy and planning; the omission of particularly vulnerable areas from loss datasets can have serious equity repercussions by potentially obscuring the severity of the risk to disasters that these areas face.

Variables related to county wealth and capacity, specifically tax revenue and the number of PDDs for which the county received PA funds, suggest the opposite. As tax revenue increases by $1,000 per capita, an observation is 0.699 times as likely (i.e., less likely) to be categorized as *Damage, No Aid*, than the reference category *No Damage, Aid*, albeit weakly significant. One possible explanation is that wealthier communities have more administrative capacity to navigate the processes to receive federal aid, even if damage is minimal or in the absence of accurate damage data [9]. This finding, however, complicates our other finding that observations in the *No Damage, Aid* category are disproportionately vulnerable. Thus, we identify mixed effects of social vulnerability on the probability of an observation falling in the *No Damage, Aid* category.

When the variable capturing county experience receiving PA funds following PDDs increases, the likelihood of falling into the No Aid categories decreases and the likelihood of falling into the Damage, Aid category increases. This finding is not surprising given that many of these grants have significant administrative burden and require high personnel, fiscal, and knowledge capacity. Applying for these grants in the past builds knowledge capacity.

Another relevant finding is that median house age increases the likelihood of an observation being categorized in the *Damage, No Aid* category relative to the reference category. One explanation is that infrastructure age may be a proxy for physical vulnerability, with older structures often sustaining greater damage. As mentioned, socially vulnerable communities often have infrastructure that is older and more prone to damage due to underinvestment in these communities [41]. In this way, our finding related to median house age could indicate that socially vulnerable counties with more physically vulnerable infrastructure are sustaining damages but not receiving federal aid.

Finally, our results indicate that damage and aid categorization are significantly impacted by FEMA region, disaster year, and political leaning. All FEMA region variables contain statistically significant RRRs for at least one of the alternative categories. (The hold-out FEMA Region is Region 1.) Of the variables with significant RRRs, most are well above 1. Observations in FEMA Regions 3 and 4 (DC, DE, MD, PA, VA, WV and AL, FL, GA, MS, NC, SC, respectively) are far more likely to be in the categories *No Damage, No Aid* and *Damage, No Aid*, than the reference category of *No Damage, Aid*. Similarly, FEMA Region 6 (AR, LA, TX) is more likely to be in the categories *No Damage, No Aid* and *Damage, No Aid* than the reference category of *No Damage, Aid.* This suggests, all else being equal, counties in FEMA Regions 3, 4, and 6 are far more likely to incur damage yet receive no aid relative to Region 1, pointing to administrative differences among the regions - consistent with the findings in Schmidtlein et al. [78]. Finally, an observation in FEMA Region 2 (NY, NJ) is 0.219 times as likely (i.e., less likely) to fall in the *Damage, Aid* category as the *No Damage, Aid* category, all else equal, perhaps pointing to more underreporting of damages in this region, or more coastal defenses that protect property - thus reducing damage - while still having an internally high capacity to apply for aid.

Our statistically significant percentage of Democrat votes RRRs indicate that a 1% increase in Democrat votes in the previous presidential election renders an observation 1.039, 1.048, and 1.017 times as likely (i.e., more likely) to fall in the *No Damage, No Aid, Damage, No Aid,* and *Damage, Aid* categories, respectively, compared to our reference category, *No Damage, Aid*. Thus, observations in the reference *No Damage, Aid* category have a populace more inclined to vote for the conservative candidate.

5.2. Stage 2

The results of the two-tier model for Stage 2 are presented in Table 3. The second column shows the coefficients, standard errors, and their statistical significance for the probit model. The last column shows the same for the truncated normal regression model.

First, results of the probit model suggest that the likelihood of a county receiving any aid increases as property damage per capita increases, though the result is weakly significant. Several of the hazard intensity and exposure variables are also statistically significant and positive in the probit model. The statistically significant positive coefficients for fatalities, precipitation, and maximum wind velocity indicate that greater fatalities, precipitation, and wind speeds increase a county's likelihood of receiving aid when damage is sustained. Similarly, the positive coefficient of the binary coastal variable indicates that coastal counties - and therefore counties with greater hazard exposure - are more likely to receive nonzero federal disaster coverage. At odds with these findings is that, as the fraction of the county area in the floodplain increases, the likelihood of receiving aid when damage is sustained decreases. The trend of higher exposure and hazard intensity leading to a greater likelihood of receiving aid when damage is sustained demonstrates the importance of the strength of the hazard when making aid determinations. Administrators may be biased by reports of high hazard intensity, and thus more inclined to award aid. It is also plausible that areas with frequent exposure to intense hazards are more prepared to apply for and navigate federal disaster aid grants.

In regards to social vulnerability, the findings from the probit model indicate that counties with a greater percentage of the population receiving public welfare assistance (e.g., TANF) are less likely to receive federal disaster aid despite sustaining damage, though the statistical significance of this result is low. This finding is further supported by the result that the likelihood of non-zero federal disaster coverage decreases as the median home age (a proxy for physical vulnerability) increases. These findings could reflect chal-

Table 3
Results of Stage 2 Two-Tier Model for predicting (1) the probability of an observation receiving nonzero coverage, and (2) the level of coverage with positive values[6,7].

	Tier 1 Probit Model			Tier 2 Truncated Normal Regression Model		
Intercept	8.787	(6.609)		0.090	(7.746)	
Disaster variables						
Fatalities (persons)	0.672	(0.342)	*	0.016	(0.025)	
Precipitation (inches)	0.113	(0.030)	***	−0.081	(0.020)	***
Property damage per capita (thousands 2019 USD)	2.919	(1.133)	*	−0.235	(0.034)	***
Storm distance (kilometers)	0.001	(0.001)		0.004	(0.001)	***
Wind velocity (meters per second)	0.118	(0.024)	***	0.029	(0.017)	
County variables						
Coastal (binary)	0.649	(0.232)	**	0.444	(0.220)	*
FEMA Region 2 (binary)	−1.388	(0.477)	**	2.245	(0.487)	***
FEMA Region 3 (binary)	−2.052	(0.425)	***	0.888	(0.463)	
FEMA Region 4 (binary)	−1.630	(0.580)	**	0.780	(0.627)	
FEMA Region 6 (binary)	−0.714	(0.612)		1.922	(0.644)	**
Land area (square miles)	3.8E-04	(2.9E-04)		−1.4E-04	(2.9E-04)	
Median house age (years)	−0.040	(0.012)	***	0.020	(0.015)	
Median household income, log (2019 USD)	−0.854	(0.549)		−0.139	(0.664)	
Number of previous PDDs with aid	0.146	(0.032)	***	−0.004	(0.036)	
Percentage of Democrat votes (%)	−0.015	(0.009)		−0.010	(0.010)	
Percentage of land in a floodplain (%)	−0.018	(0.005)	***	0.005	(0.005)	
Percentage of mobile homes (%)	0.011	(0.012)		0.029	(0.014)	*
Percentage of racial minorities (%)	0.011	(0.008)		0.011	(0.009)	
Percentage of renters (%)	0.006	(0.012)		−0.018	(0.015)	
Percentage of population 65+ (%)	1.3E-04	(0.020)		−0.022	(0.024)	
Percentage receiving PA (%) (e.g., TANF)	−0.129	(0.061)	*	0.187	(0.083)	*
Swing county (binary)	−0.038	(0.250)		−0.229	(0.283)	
Tax revenue per capita (thousands 2019 USD)	0.468	(0.127)	***	0.147	(0.070)	*
Total population, log	0.044	(0.092)		0.240	(0.110)	*
Unemployment rate (%)	0.038	(0.036)		−0.005	(0.041)	
Urban (binary)	−0.125	(0.179)		0.291	(0.227)	
Year 2009/2010	−0.036	(0.542)		0.643	(0.669)	
Year 2011 (binary)	2.186	(0.581)	***	1.239	(0.400)	**
Year 2012 (binary)	−0.537	(0.293)		0.815	(0.341)	*
Year 2016 (binary)	−0.690	(0.350)	*	0.428	(0.440)	
Year 2017 (binary)	1.039	(0.348)	**	1.679	(0.367)	***

*p < 0.5, **p < 0.01, ***p < 0.001

lenges experienced by lower-income localities with lower capacities to apply for and navigate the federal disaster aid process. The positive coefficient of the local tax revenue and previous PDDs with aid variables also support this, indicating that counties with greater local own-source tax revenue (i.e., fiscal capacity) and more experience with disaster (i.e., knowledge capacity) are more likely to receive nonzero federal disaster coverage.

Finally, the probit model results indicate that whether a county receives positive federal disaster coverage is greatly influenced by its FEMA region and the year of the storm. FEMA Regions 2 (NY, NJ), 3 (DC, DE, MD, PA, VA, WV), and 4 (AL, FL, GA, MS, NC, SC) are less likely than FEMA Region 1 (CT, MA, ME, NH, RI, VT) to receive disaster aid despite sustaining damage. Storms in 2011 and 2017 (in our dataset, the following storms are included in 2011 and 2017 data: Irene-2011, Harvey-2017, Irma-2017, and Nate-2017) are also more likely to have received aid when damage was sustained, and storms in 2016 (in our dataset, the following storms are included in 2016: Hermine-2016 and Matthew-2016) are less likely to have received aid when damage was sustained.

The findings of the truncated normal regression model indicate the marginal impact of variables on receiving higher or lower levels of federal disaster coverage when federal disaster coverage is positive. Although the Tier 1 results indicate that greater per capita damage increases the likelihood of receiving aid (relative to no aid), the Tier 2 model indicates that marginal effect of per capita damage on federal disaster coverage is negative. Similarly, as precipitation increases, federal disaster coverage decreases. Federal disaster coverage increases as the minimum distance between a county's geo-centroid and the storm's eye increases, which is also consistent with generally lower federal disaster coverage for higher intensity observations. These findings may be indicative of the costliest disasters being difficult to reimburse in the same proportion as the less expensive, smaller-scale disasters. In contrast with this finding, however, the positive coefficient for the binary coastal variable value indicates that federal disaster coverage increases for coastal counties. This again may be explained by potential administrator bias toward counties with greater exposure.

When considering socioeconomic factors, we find that as the percentage of mobile home owners and the percentage of public welfare recipients increase, federal disaster coverage increases. This suggests socially vulnerable communities may receive additional

6 Results with CDBG-DR outlays omitted are presented in Table A.2. The results are similar to the baseline estimates presented here.

7 There are 32 observations in our sample with very high federal disaster coverage (>10,000%). We conducted a sensitivity test by estimating the two-tier model without these 32 outliers (results reported in Table A.5). The results are highly similar to our baseline estimates.

benefits from the federal disaster assistance, possibly due to the federal aid programs' focus on underinsured and underprivileged communities [10]. However, when considering local capacity, we find that federal disaster coverage also increases as per capita tax revenue increases. This again reflects that counties with greater local capacity may have more administrative assets to successfully navigate the federal aid process, are more likely to meet cost-share requirements, and obtain higher rates of aid [22]. Taken with the results of the probit model, this suggests that higher capacity jurisdictions are both more likely to receive any aid following a damaging disaster and more likely to receive aid that compensates a greater proportion of damage incurred.

As the county population increases, federal disaster coverage increases. These results may represent a political dimension of federal disaster coverage, where politicians are motivated to allocate greater federal relief aid to highly populous areas, even in the absence of severe damage. It could also reflect more press coverage of disasters in populous areas.

The truncated normal regression model results again indicate that FEMA region and the year of the hurricane affect the level of federal disaster coverage. FEMA Regions 2 (NY, NJ) and 6 (AR, LA, TX) are found to receive greater federal disaster coverage than FEMA Region 1. Additionally, storms in years 2011, 2012, and 2017 (in our dataset, the following storms are included in 2011, 2012, and 2017: Irene-2011, Isaac-2012, Sandy-2012, Harvey-2017, Irma-2017, and Nate-2017) also receive greater federal disaster coverage. These results suggest that the year of a disaster has a significant effect on how funding is allocated. Possible explanations for this variation are differing levels of media presence surrounding these disasters, differing levels of political will to support recovery, and finally, differences in how aid is administered. Notably, CDBG-DR is not a standing program, and is authorized by Congress on a case-by-case basis through supplemental appropriation. While, presumably, the core tenants of the authorization bills remain similar, each authorization could have procedural differences. Similarly, much of the fund disbursements for CDBG-DR are dictated by state decisions, and different states likely have different funding prioritization.

6. Conclusion

While much research has examined the determinants of disaster damage or federal disaster grants in the past ([39]; [3,5,92]), little is known about the extent to which the proportion of locally incurred damages are covered by federal aid after a disaster. In this paper, we present the first study that examines federal disaster coverage in relation to various county and disaster characteristics. Considering the fragmentation of federal disaster grants, we focus on the outlays from the three largest federal disaster recovery programs to gauge the overall transfers a county receives following a major hurricane shock. Studying the aggregated outlays as a proportion of disaster damage provides necessary context to understand how much of the burden of recovery is actually borne by localities. It is also more reflective of the pragmatic effect of federal aid at the county level and could ultimately help explain differential recovery trajectories.

Results from Stage 1 of our analysis show, as expected, that as hazard intensity increases, counties are more likely to experience damage and receive aid, and this is consistent with past findings [11,92]. Interestingly, however, as the area of the county in the floodplain increases, the county is less likely to incur damage and receive aid than to incur no damage yet still receive aid, though the effect is small (yet significant). This could point to greater intentional adaptation in flood-prone areas, and more knowledge capacity in these areas to apply for aid. County observations that are more likely to incur no damage yet still receive aid exhibit both higher social vulnerability and higher fiscal and knowledge local capacity (as measured by own-source tax revenue and experience receiving PA funds in the past) compared to the other categories of observations. It is possible that these areas are, in fact, experiencing damage and are consequently receiving federal disaster aid, but that these damages are underreported in the storm damage dataset. This may suggest that areas of high social vulnerability are disproportionately underreported in the NWS Storm Events Database and in SHELDUS. This pattern would introduce difficulties and pose equity concerns when attempting to evaluate the trends and correlates of disaster damage and federal disaster coverage. This is additionally problematic given that prior literature consistently demonstrated how socially vulnerable populations are over exposed to hazards and unserved by disaster aid [4,92,93]. There is also anecdotal evidence of higher capacity counties receiving aid despite little to no damage [24], so both underreporting of damage and disproportionate targeting of resources to higher capacity counties may be occurring.

Stage 2 of our analysis demonstrates that, for those observations where damage is greater than zero, the probability of receiving any coverage increases with increasing storm severity, damages, and hazard exposure. In terms of social vulnerability metrics, observations with higher percentages of the population receiving public assistance (e.g., TANF) were less likely to receive aid, perhaps indicating challenges related to local capacity to navigate the bureaucratic processes to access any aid. In line with local capacity influencing the receipt of any aid, results indicate that the probability of a county receiving aid increases as county tax revenue increases and experience receiving PA funds following PDDs increases. This supports past findings that demonstrate the importance of local capacity (i.e., resource, personnel, and knowledge capacity) in applying for and administering disaster aid and federal grants more broadly [11,94].

For those counties that do receive aid, federal disaster coverage decreases as precipitation and per capita damage increases, suggesting the costliest disasters are most difficult to reimburse. Our findings regarding social vulnerability indicators suggested that more socially vulnerable areas (in terms of more mobile home owners and higher percentages of residents receiving public assistance) received higher coverage. We find that local capacity is again important, with higher tax revenues corresponding to higher federal disaster coverage. We also find that FEMA region and event year are consistently important, which could point to administrative differences between regions and prior experience with disasters and subsequent aid application.

Our findings show that local capacity is important across all stages of our analysis. First, we find that higher local capacity increases the likelihood of an observation being in the *No Damage, Aid* category as compared to the *Damage, No Aid* category. This suggests that higher capacity counties are more likely to be able to access federal aid, even in the absence of reliable damage reporting. In

Stage 2, we provide more evidence for this, showing that greater local capacity increased the likelihood of a county with damage receiving any aid. We then demonstrate that local capacity is not just important for accessing aid, but also for the level of aid coverage. Counties with higher local capacity corresponded to significantly higher rates of coverage. These results suggest that areas that already have access to greater resources and greater ability to respond to disasters are more likely to receive aid and more likely to receive more aid relative to damages. This result aligns with past observations and findings (e.g., Ref. [9,95]). In this way, the federal disaster aid process may perpetuate and even exacerbate inequalities among jurisdictions by contributing to a process where capacity begets capacity, and areas that are already more resourced have an additional leg up in the recovery process.

While an important first step in assessing federal disaster coverage, there are several limitations. Firstly, as mentioned, there are known issues in the data quality of SHELDUS damage data used, including significant data not missing at random [91]. In light of these data challenges, it is not clear how trends in federal disaster coverage would look in our analysis if we did have perfect damage data. This points to an important area of future work in which additional damage data can be collected to either supplement or replace current SHELDUS damage estimates. For example, damage estimates from internal FEMA damage assessments that help aid PDD determinations (if available), IHP damage assessments, and National Flood Insurance Program (NFIP) damage assessments could augment the models' current damage estimates. Note that IHP and NFIP recipients reflect only a portion of a region's population. An additional option could be to impute missing damage data, as suggested by Gallagher [91]. Multiple imputations of missing data could be used to validate the robustness of results. Because areas that received aid but had no reported damage (and were suspected to be missing data) were predominantly socially vulnerable, additional damage estimates or imputations for these areas may alter some Stage 2 findings.

Another limitation is that this work investigates only three of over 30 federal disaster aid programs. We also elected to combine the funds from these three programs in our analysis, which could obscure differences between the programs, though we do this because we are curious about cumulative aid received locally. This research could be expanded by evaluating federal disaster coverage with different or additional disaster aid programs, which could again reveal new patterns and potential inequities in federal disaster coverage. In line with this limitation related to variables included, we were also selective in the socioeconomic variables that we included, focusing on race, age, and income as key measures of social vulnerability. We know, however, that there are other variables that may be salient for social vulnerability including disability status, gender, and housing tenure [39,43,96]. In the future, inclusion of additional variables could reveal new dimensions of social vulnerability that may be relevant to federal disaster coverage.

This work provides several other opportunities for future work. While we presume that federal funding is critical for community disaster recovery, this work does not begin to provide evidence to this effect. In the future, an investigation could be conducted linking federal disaster coverage to recovery pathways to quantify how federal disaster coverage lends itself to recovery speed and levels. For example, there is existing work that has assessed the effectiveness of CDBG-DR funds in housing recovery after Hurricane Katrina [97], but such a study of federal disaster coverage overall does not exist. Future work could also consider how the speed of federal disaster coverage interacts with the recovery process over time.

Overall, our findings suggest disparities in disaster damages reporting in a popular disaster loss database (SHELDUS) and in federal aid disbursement among counties. In particular, areas with higher social vulnerability and lower local capacities are more likely to receive less federal disaster coverage and, potentially, have unreported losses in damage datasets. Federal agencies (such as FEMA and HUD) should ensure these communities have sufficient access to and support during the federal aid application process to improve recovery outcomes.

CRediT authorship contribution statement

Linda Waters: Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing, Funding acquisition, Conceptualization. **Kelsea Best:** Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Qing Miao:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Meri Davlasheridze:** Conceptualization, Methodology, Writing – review & editing. **Allison C. Reilly:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2024.104430.

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