ABSTRACT

Title of thesis: WHEN FEDERAL DISASTER AID DOESN'T SUFFICE: AN ANALYSIS CONSIDERING DISASTER AID RELATIVE TO SUSTAINED DAMAGE

Linda Jennifer Waters, Master of Science, 2023

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The level of outlays that individuals and communities receive following a disaster strongly influences the rapidity and the degree to which they ultimately recover. While there is no prescribed formula for the level of cumulative federal aid a community will receive following a disaster, 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. However, a simple analysis of the fraction of damages that are later restituted by federal disaster aid (which we call "federal disaster coverage") for all major hurricanes hitting the U.S. between 2008 and 2017 shows that this fraction is highly variable. For some storms, the county-level variation is more than six orders of magnitude. In this work, we investigate the county-level correlates of higher rates of federal disaster coverage. We do this by answering (1) What community and hazard characteristics are important predictors of counties that receive aid but that do not incur damage? and (2) Where damage is incurred, what community and hazard characteristics in a county 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 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 and less local capacity. We also find that federal disaster coverage decreases as per capita damage increases, which has two interpretations. First, this could suggest that more severe disasters receive less marginal aid than less severe disasters. Alternatively, should damage among counties be held equivalent, the result suggests that less populous counties receive less federal disaster coverage. This may reflect the predominance of federal disaster aid being aimed toward the recovery of public infrastructure, of which rural communities have less. Our findings regarding how social vulnerability relates to federal disaster coverage are mixed. Some variables show that greater social vulnerability increases the likelihood of receiving higher federal disaster coverage, while others show a decrease. We find that greater local capacity consistently increases the likelihood of receiving more federal disaster coverage.

Overall, our findings suggest some level of disparities in disaster loss reporting and federal aid disbursement among counties. In particular, areas with higher social vulnerability and lower local capacities are more likely to have unreported losses and receive less federal disaster coverage. 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 outcomes.

# WHEN FEDERAL DISASTER AID DOESN'T SUFFICE:
# AN ANALYSIS CONSIDERING DISASTER AID RELATIVE TO SUSTAINED DAMAGE

by

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Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Master of Science
2023

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# Acknowledgements

This work would not have been possible without the help and support of many in my life. I would first like to express my earnest appreciation for and thanks to my advisor, Dr. Allison Reilly, for her patience, guidance, and support during this project and throughout my graduate education. I am also extremely grateful for my committee members, Dr. Michelle Bensi and Dr. Deb Niemeier, for offering their time, expertise, and patience both on this work and in my education. I would like to thank Dr. Kelsea Best and Dr. Qian He for their incredible feedback on this work, advice, and support. I deeply appreciate the amazing friendship and camaraderie of my groupmates, Adriana, Diako, and Mohammadreza, and friends, Constantinos, Colin, Nneoma, and many others. Finally, I would like to thank my family, John, Dr. LaMarca, and Tippy for their unwavering support and encouragement.

This work was supported by NRT-INFEWS: UMD Global STEWARDS (STEM Training at the Nexus of Energy, WAter Reuse and FooD Systems) that was awarded to the University of Maryland School of Public Health by the National Science Foundation National Research Traineeship Program, Grant number 1828910, CRISP 2.0 Type 1: Accelerating restoration through information-sharing: Understanding operator behavior for improved management of interdependent infrastructure that was awarded to the University of Maryland by the National Science Foundation Critical Resilient Interdependent Infrastructure Systems and Processes Program, Grant number 1832642, the Clark Graduate Fellowship Initiative, the Dean's Fellowship in the Department of Civil and Environmental Engineering, the Lieutenant General John W. Morris II Graduate Fellowship, and the Flagship Fellowship at the University of Maryland. Any opinions, findings, conclusions or recommendations expressed in this publication are those of the author and do not necessarily reflect the views of these institutions.

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# List of Abbreviations and Acronyms

| | |
|---|---|
| CDBG-DR | Community Development Block Grant Disaster Recovery |
| CPI | Consumer Price Index |
| FEMA | Federal Emergency Management Agency |
| HUD | Department of Housing and Urban Development |
| IHP | Individuals and Households 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 |
| SNAP | Supplemental Nutrition Assistance Program |
| 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 (CRS, 2022; HUD, 2023). Climate change and permissive land-use policies are often cited as the main drivers of this escalation in disaster spending, but some scholars have also identified the role that politics, local capacity, and population have in higher outlays per capita (Cutter & Emrich, 2005; Drakes et al., 2021; Reeves, 2011; Shi & Varuzzo, 2020). While there are many programs in the U.S. through which relief funds may flow, most funds for federally-recognized disasters come from programs administered by the Federal Emergency Management Agency (FEMA) and the Department of Housing and Urban Development (HUD). 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 aid programs. While there is no prescribed formula for the level of cumulative federal aid a community will receive following a disaster, 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. In this case, more damage intuitively implies more aid to an affected area, but this assumption has not previously been investigated quantitatively.

In this work, we are interested in the fraction of damages that later are restituted by federal disaster aid (which we refer to as "federal disaster coverage"), and what the county-level correlates are of higher rates of federal disaster coverage. We know from the insurance literature that the fraction of damage that is later restituted through private insurance is highly predictive of the strength and speed of recovery (Peacock & Girard, 1997), and, presumably, 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. Take, for instance, the damage reported during Hurricane Harvey in 2017 (Figure 1a) and the cumulative 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 a county-level (Figure 1b). Unsurprisingly, areas with high damages are also areas that received more aid. However, if we compare the ratio of aid to damage, we find that this fraction ranges from 0.005 to 3000 - a six-order-of-magnitude difference (Figure 1c). Many storms produce similar results.

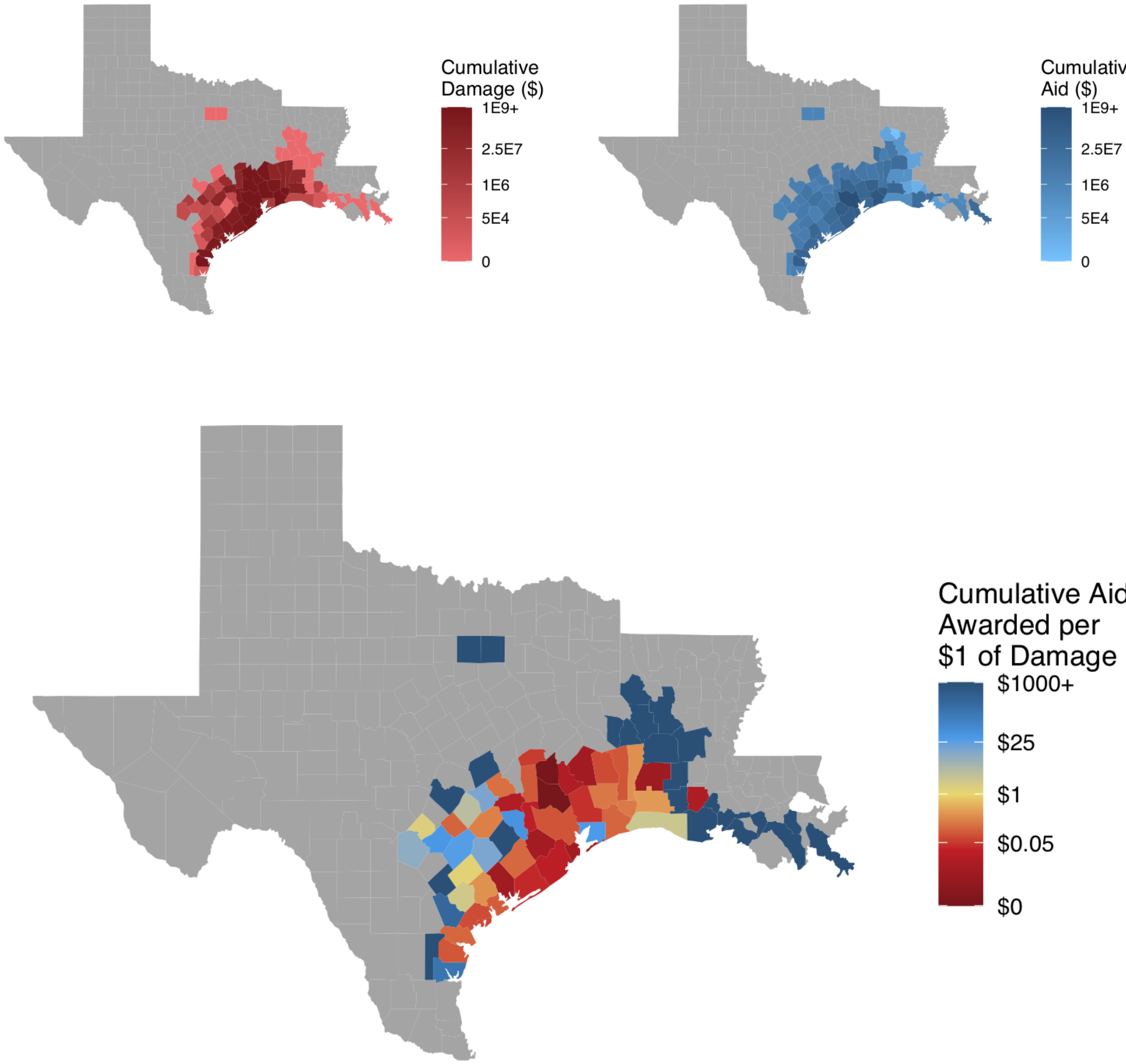


**Figure 1**. County-level comparison of damage, aid, and federal disaster coverage for Hurricane Harvey (2017). Cumulative damage by county (**1a**), Cumulative aid by county (**1b**), and Cumulative federal disaster coverage (**1c**). The map was generated using the R package '*maps*' (Becker et al., 2022). The base map in this figure is from 2022 TIGER/Line Shapefiles, prepared by the U.S. Census Bureau. It is in the public domain and is not copyrighted (U.S. Census Bureau, 2022).

While such a broad range of federal disaster coverage is unexpected, it is not surprising that there is least some variation, and there are multiple possible explanations. 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 (FEMA, 2023c). Conversely, socioeconomic 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 allocating administrative resources to navigate the grant application process (Domingue & Emrich, 2019). Similarly, poorer regions and communities of color tend to receive less federal assistance to invest in mitigation (Hersher, 2019; Seong et al., 2022; Siders, 2019). They also tend to be overexposed to hazards relative to wealthier and whiter communities due to a combination of exclusionary zoning, discrimination in housing, and simply that higher-risk locales have lower-valued land (Arcaya et al., 2020; Atreya et al., 2015; Hendricks & Van Zandt, 2021; Ueland & Warf, 2006). All combined, this can lead to more damage, but potentially less aid.

Conversely, a wealthier county might be expected to receive more aid than a poorer county, all other things being equal, because it is expected to have more assets and thus have more opportunity for asset damage (Hallegatte et al., 2020). 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 (OpenFEMA, 2021b, 2021a). 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 (Howell & Elliott, 2019). Thus, we know that wealth and socioeconomic factors can influence damages and aid, but this relationship is complex.

The variety of purposes, eligibility, availability, accessibility, and program rigidity of federal disaster programs means that federal disaster coverage can be highly spatially variable and greater than one (indicating that the amount of aid received is greater than damages incurred). In this work, we investigate factors that influence federal disaster coverage to understand why some affected areas receive more federal disaster coverage than others. More specifically, we answer the questions:

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

While the factors that influence disaster damage and subsequent federal aid have been explored separately in past research, 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 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 (Despart, 2022).

To explore our research questions, we develop multinomial logistic regression models over two stages. In the first stage, we use an ordinal logistic regression 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. This is important to understand why some counties receive significant amounts of aid despite little or no damage, while other counties that are greatly affected receive less aid. In the second stage of the analysis, we fit a separate regression model to identify the correlates of having a high (or low) federal disaster coverage rate. All counties without damage are excluded from this analysis to avoid having federal disaster coverage values of infinity. 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), with the rationale being that these are the largest grant providers of recovery funds. 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.

The following section, Section 2, reviews federal disaster aid programs and presents a conceptual model of the relationships between a myriad of factors influencing federal disaster coverage based on the current literature. Sections 3 and 4 describe the data and methodology, respectively. Sections 5 and 6 present results and discuss our main findings. We draw conclusions and suggest avenues for future work in Section 7.

# 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 to support program administration. At the time of writing in 2023, the Federal Emergency Management Agency has set a threshold of $1.77 of per capita damage at the state level and $4.44 of per capita damage at the county level to be eligible for a PDD, although some other factors may be taken into consideration (FEMA, 2023b).

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 issued to affected states for particularly destructive disasters by Congress. Between 2008 and 2017, more than $153B (2022 USD) were issued through these programs (see Figure 2). 81% of these funds were congressional supplemental appropriations, meaning that the funds were unplanned during the annual federal budgeting process (CRS, 2022; OpenFEMA, 2021b, 2021a; HUD, 2021).

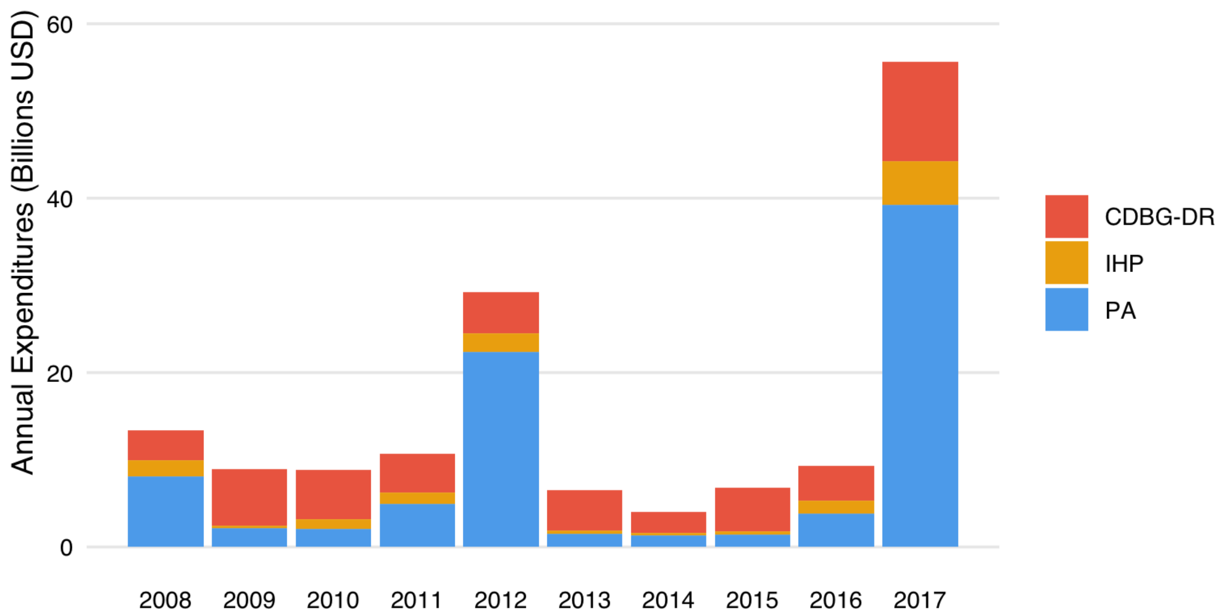


**Figure 2**. Annual Expenditures for CDBG-DR, IHP, and PA from 2008 to 2017 (HUD, 2021; OpenFEMA, 2021a, 2021b)

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 (OpenFEMA, 2021b).

IHP is awarded to eligible individuals and households impacted by disasters. Recipients of IHP receive direct financial assistance up to $36,000 to address immediate household expenses that are un- or underinsured. Depending on many factors, this could include funds for lodging or rental assistance, home repair assistance, and funeral expenses, among other expenses. The grants are not intended to make the recipient whole, but rather ensure basic needs are met following a disaster. Indeed, Kousky (2021) 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 (OpenFEMA, 2021a). IHP does not have cost-share requirements.

HUD 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 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 (Burton, 2015; Drakes et al., 2021). It is also the measure that is used, nearly exclusively, by the U.S. federal government to determine whether federal intervention is warranted via a per capita damage 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 (Figure 3). More assets, higher-valued assets, less protected assets, more fragile assets (e.g., buildings built to lower code) (Figure 3, Arrow 1), and stronger hazards all lead to more damage (Figure 3, Arrow 2).

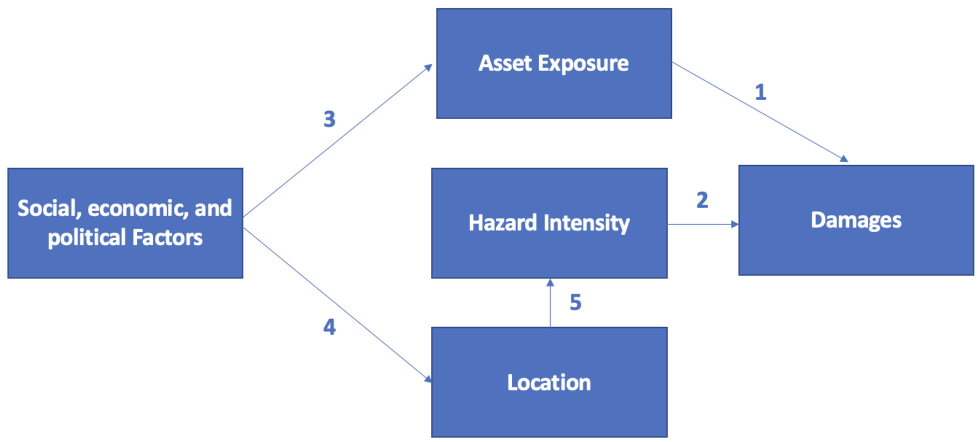


**Figure 3**. Conceptual model of factors influencing disaster damage.

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 (Figure 3, Arrow 3), and even the intensity of hazard forcing an asset is likely to experience (Figure 3, Arrows 4 and 5). The relationships between these factors, however, are complex and interrelated. As an 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 direct result of larger and newer homes and, consequently, higher property improvement values (Hallegatte et al., 2020). 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 (Cutter et al., 2018). Affluent regions also benefit from more local, state, and federal investment in public infrastructure, including schools and civic buildings (Zuk et al., 2015). This combination of more assets and higher-valued assets, in theory, has the potential to lead to more damage.

However, affluent communities possess multiple factors that moderate this risk compared to communities with lower incomes. First, because of their greater potential for damage (as measured by economic value alone), the U.S. Army Corps of Engineers (USACE) builds more protective infrastructure around and FEMA awards more mitigation grants to affluent areas (Anguelovski et al., 2016; Seong et al., 2022; Siders, 2019). This, in part, stems from the benefit-to-cost ratio of these protective investments simply being higher in these areas (McGee, 2021). A 2021 Urban Institute report found that only recently have “innovative” benefits been included by these agencies - meaning benefits ranging from ecosystem service benefits to preservation of social networks - but this has been more of an exception than a rule (Junod et al., 2021). Furthermore, FEMA mitigation grants often require a local cost-share, and USACE requires the community to pay for future asset maintenance; thus, many hazard mitigation options are financially out-of-reach for socially-vulnerable regions, even if they were to have the local administrative capabilities to apply for and manage these grants (Siders & Gerber-Chavez, 2021). Many do not (Li & Landry, 2018; Sadiq & Noonan, 2015).

In addition to receiving less physical protection from hazards, socially-vulnerable communities tend to have infrastructure, including homes, schools, and even municipal water systems, that are more fragile and thus more physically vulnerable to hazards compared to more affluent regions. This is partially a result of a lack of sustained investment in maintenance over time, sometimes due to financial limitations, but also due to diminished political and social will to invest in these communities (Hendricks & Van Zandt, 2021). Socially-vulnerable communities have endured years of political and social disenfranchisement in the risk management process

(Bunting, 1995). Due to historic discrimination and institutionalized racism, low-income areas are also more likely to have higher percentages of racial minorities, adding an additional layer of marginalization and reduced social, political, and economic capital (Braveman et al., 2022; Galster, 1992; Galster, 2012; Jan, 2018; Solomon et al., 2019). For instance, the 2022 Jackson, Mississippi water crisis led to its residents being without potable water for weeks following historic winter storms and, later, summer flooding. The city is more than 80% Black and, at the time, had a rate of pipe breaks of 55 breaks per 100 miles of line - 360% greater than what is deemed safe for potable water (U.S. Census Bureau, 2020; U.S. Environmental Protection Agency Region 4 et al., 2022). While the post mortem is still ongoing, there is general consensus that a 2010 political refusal by the state's Bond Commission to take up the issue of whether to issue bonds to finance repairs and investments in Jackson ensured later catastrophic failures (Goldberg, 2022).

In part due to this lack of investment, infrastructure assets in socially-vulnerable areas are typically older, of lower quality, and built to older engineering standards, making them more susceptible to severe damage as a result of a hazard (Fothergill & Peek, 2004). This can contribute to both short- and long-term disparities in hazard risk, with serious implications for livelihoods, health, and wellbeing (Howell & Elliott, 2019). For example, no public housing in Miami had window protection during Hurricane Andrew in 1992. This resulted in thousands of public housing residents being displaced from their homes due to damage and sheltered in tent cities after the storm (Morrow, 1999). As another example, mobile and manufactured homes are far more likely to be occupied by older, poorer, and immigrant populations, and to be catastrophically destroyed during a hurricane compared to traditional housing because they are of poorer construction quality. While these homes are often situated in areas that make them particularly vulnerable to wind and storm surge, residents have historically received minimal investments from either public or private institutions to bring their homes up to modern engineering standards (e.g., hurricane tie downs). The cause of this is that mobile and manufactured homes are personal and not real property, meaning it is challenging for these institutions to capture the value of these investments (Prasad & Stoler, 2016). These are just a few examples of how a lack of social and political will has made infrastructure in socially-vulnerable regions more vulnerable to hazards and, consequently, potentially more likely to experience damage.

Finally, social, economic, and political factors strongly influence and reinforce the geographic boundaries of race and class. These boundaries, in turn, influence the strength and the frequency of hazards to which their residents are exposed (Fig. 3, Arrows 4 and 5). Following the U.S. Civil War, many newly incorporated towns, such as Princeville, North Carolina, and North Brentwood, Maryland, were founded and settled by formerly enslaved people and Black veterans. These towns, uncoincidentally, were and continue to be highly-exposed to flooding, making the land both undesirable for White residents and economically attainable for the formerly enslaved (Bidgood, 2016). Later, 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. This policy, repealed only in 1968, led to decades of divestment in many urban areas while exacerbating exposure to hazards in socially-vulnerable regions (Braveman et al., 2022; Hendricks & Van Zandt, 2021). The combination of more renters and urban divestment has left these neighborhoods with buildings built to lower standards, worse air quality, heat islands, and, also, more exposed to hazards. For instance, Linscott et al. (2021)

found that the boundaries of 2010 Nashville Floods followed many boundaries established by redlining, and that socially-vulnerable populations continue to comprise these neighborhoods today. The lines of segregation are still present in many U.S. cities; in Baltimore, Maryland, for example, life expectancy today follows the outlines of past boundaries, with redlined neighborhoods having a life expectancy seven years less than non-redlined ones (White, 2020).

Many argue that socially-vulnerable populations today are overexposed to hazards relative to people in more affluent areas simply as a result of economics (Lee & Jung, 2014). High threat of hazards depreciates land values, and these less expensive areas are often some of the only areas affordable to low income and socially-vulnerable populations (Lee & Jung, 2014). For example, Prasad and Stoler (2016) found that 27% of mobile and manufactured homes in South Florida are in areas of high threat of flooding or storm surge, largely due to the lower cost of land in these areas. Mobile and manufactured homes are particularly vulnerable to flooding and surge. However, exclusionary zoning is among the most insidious factors for ensuring racial and class boundaries persist and that socially-vulnerable populations are unable to relocate to lower hazard risk areas (Whittemore, 2020). 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 (Long & Rice, 2019). Political leaders are frequently ousted when they propose to alter the status quo of these policies (Span, 2001). These areas have more desirable amenities, not limited to more green space and trees, higher quality schools, and less crime, but often these areas are less threatened by hazards (Greene & Ellen, 2020; Span, 2001). Exclusionary zoning ensures these conditions persist.

*2.2.2 Factors influencing aid*

By design, the level of federal disaster aid that a county receives strongly depends on the level of damage a region sustains (Figure 4, Arrow 1) (Domingue and Emrich, 2019). For instance, Miao et al. (2023) explore the level of federal outlays across all U.S. counties while accounting for the complex relationship between hazards and damage. They find that stronger hazards lead to more damage, and more damage leads to more aid for all federal aid programs, including those which are loan-based and for mitigation purposes. This is expected as federal disaster determinations and the programmatic design of aid programs are primarily based upon damage.

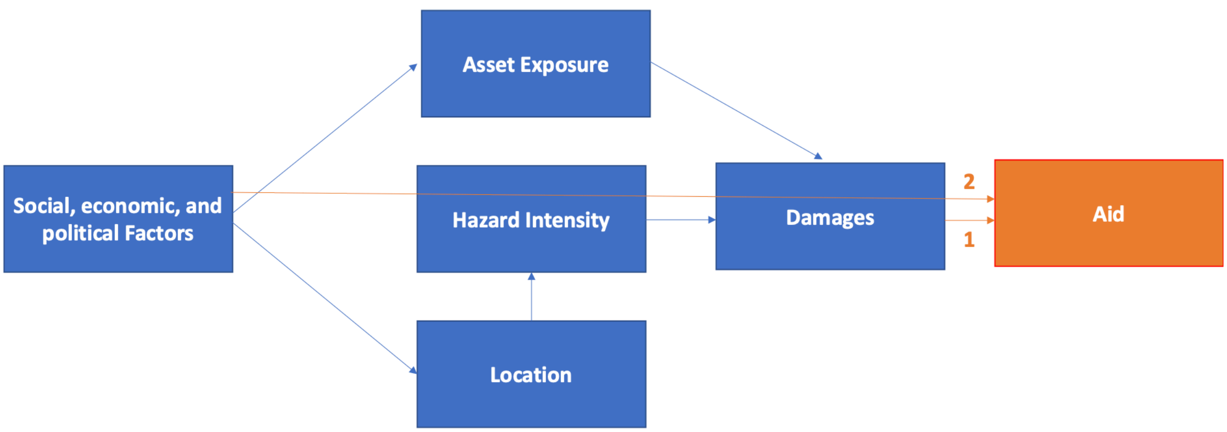


**Figure 4**. Conceptual model of influencing factors of federal disaster aid.

However, as with damages, federal disaster aid is strongly dependent on social, economic, and political factors (Figure 4, Arrow 2). While the research in this space is burgeoning, it is clear that more affluent regions receive more disaster aid (Emrich et al., 2022) and that the remaining socioeconomic factors have mixed effects on receipt of disaster aid (Domingue and Emrich, 2019). These effects vary among aid programs. It is unsurprising that wealthier areas receive more aid, *ceteris paribus*. 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 (Peacock & Girard, 1997). There is significant evidence that many wealthier jurisdictions place considerable emphasis on this procurement of federal funds, many with staff devoted to this task (Smith et al. 2013, Brody et al. 2010). Conversely, low internal capacity is a widely acknowledged barrier for why low-resourced communities continue to receive less federal assistance (GAO, 2022). To address this, in August 2022, FEMA increased its "small project" maximum for PA from $139,800 to $1M; 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 (FEMA, 2023b). Finally, a requirement for receiving aid is having a hazard mitigation plan in place prior to the disaster (Carter et al., 2019). Despite being an onerous undertaking for many jurisdictions, plans are increasingly put in place simply so that funds can be doled out later - 85% of Americans live in a jurisdiction with mitigation plans in place (FEMA, 2023a). However, states with "enhanced mitigation plans" in place prior to the disaster - mitigation plans that are especially comprehensive and onerous to produce - are eligible for additional disaster aid. As of the end of 2022, only 15 states have enhanced mitigation plans in place (FEMA, 2023a), though more research is needed to understand why they sought this designation.

Multiple recent studies have found mixed effects of other socioeconomic factors on the receipt of aid. Domingue and Emrich (2019) model the influence of a wide range of socioeconomic, demographic, and built environment factors on PA outlays by year. 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. 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 (Kamel, 2012). This is likely tied to the ease in which potential applicants were able to apply for these funds (Hooks & Miller, 2006). More recently, several trends - specifically, trends pertaining to obtaining IHP assistance, housing repair and replacement assistance, and other needs assistance - were found to persist, with communities of color in particular typically receiving less IHP (Emrich et al., 2022).

Additional social and political factors have been found to influence outlays. For instance, Eisensee and Strömberg (2007) find that increased media coverage, which likely places more pressure on federal administrators to effectively respond to a crisis, drives 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, especially as they are direct payments to communities by decision-makers in times of crises. Electorally-competitive states have been found to be more likely to receive a PDD following a disaster - and thus qualify for federal disaster assistance - than less electorally-competitive states, and PDDs are more likely to be declared during election years (Sobel et al., 2007; Reeves, 2011). Federal disaster expenditures in states with congressional representation on FEMA oversight committees are also found to have greater disaster expenditures (Garrett & Sobel, 2003). Finally, political ideology and leanings within communities influence local receptiveness to federal assistance and preferences over which level of authority should oversee risk management and disaster recovery (Wehde & Nowlin, 2021). 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 nearly 50% 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 (Botzen et al., 2016). Unfortunately, this preparation can be moderated by conservative beliefs that the threat of some hazards tends to be lower (Saleh Safi et al., 2012).

### *2.2.3 Factors influencing federal disaster coverage (Conceptual model)*

Our two primary research questions aim to identify community and hazard characteristics of counties that receive aid but incur no damage (Stage 1) and factors that influence the degree of county-level federal disaster coverage (Stage 2). These questions are investigated separately to absolve issues related to having a zero in the denominator for federal disaster coverage (i.e., aid over damage). While existing literature has investigated hazard, social, economic, and political factors that contribute to disaster damage (Figure 3) and federal disaster aid (Figure 4) separately, we explicitly explore how these factors influence the fraction of losses that the federal government restitutes (Figure 5). While it is clear that federal aid generally increases as damages increase (Domingue and Emrich, 2019), 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. We posit four hypotheses related to Stage 1 and Stage 2 of the analysis.

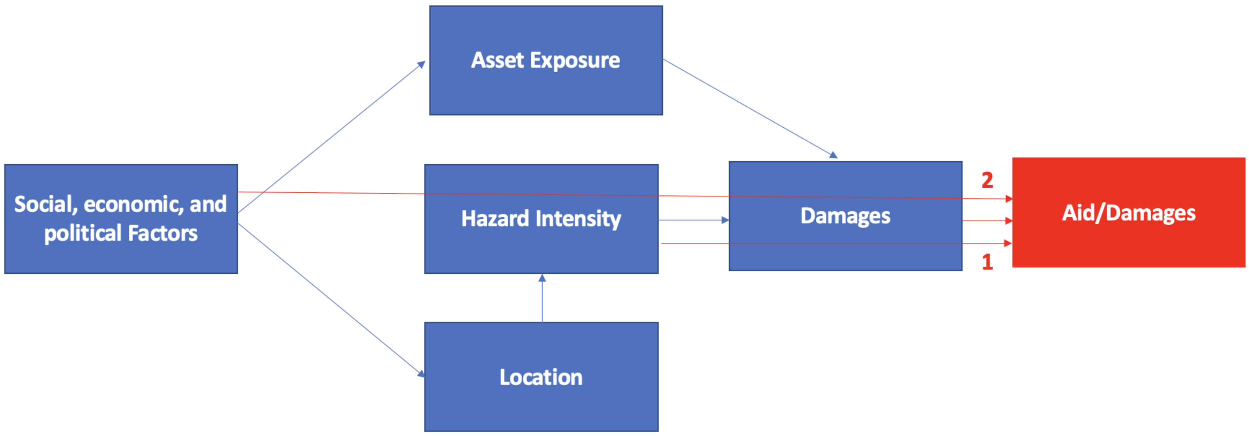


**Figure 5**. Conceptual model of influencing factors of federal disaster coverage.

**Hypothesis 1:** We hypothesize that wealthier and whiter counties and counties with higher capacity are more likely to receive aid yet sustain no damage, regardless of hazard intensity. (Investigated in Stage 1.)

The effect of factors related to hazard intensity on explaining why some counties receive aid yet sustain no damage is challenging to predict. We presume that weaker hazard intensity is a necessary but insufficient condition to receive this classification, as weaker hazards are tied to less damage. The reasons why a county would receive aid but not sustain damage are likely more so due to social, economic, and political factors. Ultimately, our rationale for this hypothesis is that, 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 (Peacock & Girard, 1997).

**Hypothesis 2:** We hypothesize that the influence of hazard intensity on federal disaster coverage is ambiguous. (Investigated in Stage 2.)

It is well established that more powerful storms lead to greater outlays *ceteris paribus* (Grube et al., 2018). One driver of this is that more destructive disasters are more politically motivating than less destructive disasters, which would not only increase the likelihood of receiving a PDD in the first place (Garrett & Sobel, 2003), but also increase media coverage and public pressure on political and bureaucratic leaders to acquire or allocate more funding for recovery (Eisensee & Strömberg, 2007). For example, state governors may request higher FEMA cost-shares for PA for exceptional cases, raising FEMA's share from the standard 75% of damages to up to 90% of damages (GAO, 2012). Additionally, 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 (Elsner et al., 2011; Grube et al., 2018; Hamid et al., 2010; Jonkman et al., 2009; Knighton et al., 2020; Zhai & Jiang, 2014). However, as storm intensity increases, the rates at which damage and aid increase relative to each other are unknown. 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.

**Hypothesis 3:** We hypothesize that the influence of social, economic, and political factors on federal disaster coverage are mixed. (Investigated in Stage 2.)

Areas with lower capacity and higher rates of socially-vulnerable populations, such as lower-income, minority, foreign-born, renters, and less educated 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 (Cutter & Emrich, 2005; Drakes et al., 2021; Grube et al., 2018; Hooks & Miller, 2006; Kamel, 2012). For these reasons, we 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. These populations often own and occupy less valuable property, resulting in fewer sustained damages (Drakes et al., 2021). At the same time, these populations are also more likely to live in high-risk areas and are less likely to obtain insurance or employ mitigation measures, increasing their exposure (Dixon et al., 2017; Drakes et al., 2021; Emrich et al., 2020; Gall & Friedland, 2020; Knighton et al., 2020; Multihazard Mitigation Council, 2017). Thus, even though increased social vulnerability and reduced local capacity decrease the likelihood of receiving federal aid, its impacts on damage are ambiguous. Because of this, it is difficult to predict if greater social vulnerability and reduced local capacity increase or decrease federal disaster coverage.

**Hypothesis 4:** We hypothesize that social factors within bureaucracies will be relevant in explaining federal disaster coverage. (Investigated in Stages 1 and 2.)

Schmidtlein et al. (2008) found FEMA regions (i.e., administrative districts) to be highly relevant for explaining why some counties receive disaster declarations and higher outlays. Consequently, we expect program implementation and administration to vary by region, with some regions receiving significantly more aid on a per damage basis.

# 3 Data

The 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 or receive aid. FEMA data for IHP and PA are collected from FEMA's Open Source database (OpenFEMA, 2021b, 2021a), and then are aggregated to the county-level. Note that some PA grants are issued to state agencies, so it is not obvious to where these funds are ultimately distributed. These records are excluded from our analysis. CDBG-DR data are scraped from CDBG-DR project plans, and then aggregated to the county-level. CDBG-DR project plans report, 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. It is possible, however, that the work 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 project spend plans were not available for Hurricane Irma funds for Florida, Hurricane Irene funds for New Jersey, Hurricane Sandy funds for New Jersey, and for 1.1% of Hurricane Harvey funds for Texas. 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 to missing data, as a robustness check, we model federal disaster coverage both with and without CDBG-DR data included. (Results without CDBG-DR included are presented in Appendix 1 and highly align with results that include

CDBG-DR outlays.) Counties included within a PDD but that do not receive aid are assigned $0 in aid. The final dataset consists of 1,944 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 (CEMHS, 2022). From this dataset, we collected property damages and fatalities for each county-PDD pairing. SHELDUS data are imperfect. First, the bulk of SHELDUS records are derived from the Storm Events Database (NCEI, 2022). The spatial scale used by this database is a mix of counties and National Weather Service (NWS) Public Zones. When an NWS zone is used, and when this zone intersects multiple counties, SHELDUS distributes losses evenly among these counties. Further, past research has found that SHELDUS tends to underestimate losses (Gall et al., 2009). 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 influenced by our conceptual models and literature on the determinants of disaster damage and disaster aid. Hurricane intensity data is primarily collected using Anderson et al.'s (2020a, 2020b) open-source R packages *'hurricaneexposure'* and *'hurricaneexposuredata.'* For each county-PDD pair, we collect the maximum 10-meter 1-minute sustained wind speed at the county's population centroid. The package leverages the Willoughby hurricane wind speed model to interpolate these figures (Anderson et al., 2020c, Willoughby et al., 2006). 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 three days after the hurricane made landfall, is 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 (Eggleston, 2022).

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 (FEMA, 2021). We also include a binary indicator for whether the county is coastal. Finally, we include the total land area of a county to control for its size (U.S. Census Bureau, 2011).

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. (2008) 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 five FEMA regions, and thus we constructed five time-invariant binary variables to indicate to which FEMA region a county belongs (OpenFEMA, 2022). Because there are only two county-PDD observations in Region 5, these observations are redesignated to a neighboring region, Region 3. We also construct a variable for each county-PDD pairing that is a count of the number of PDDs for which the county received aid between 1995 and the PDD of interest. 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 (U.S. Census Bureau, 2021).

We capture the condition of the built environment using four indicators. These indicators include the percent of houses that are mobile or manufactured homes, the median age of county homes, and the percent of the population who are renters (U.S. Census Bureau, 2020). To indicate whether the county is rural or urban, we use the U.S. Department of Agriculture 2013

Rural-urban Continuum Codes (USDA ERA, 2020). 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 percent of the population that is nonwhite, the percent of the population that is 65 years of age and older, median household income (logged), the percent of households receiving public assistance through at least one social welfare program (e.g., Supplemental Nutrition Assistance Program (SNAP)), and the unemployment rate of the county (U.S. Census Bureau, 2020). 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.

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 percent of the county's population that voted for the Democratic presidential candidate and whether the county was a swing county (Leip, 2019). A swing county is defined as one in which the difference between the percent of the county that voted for a Democratic candidate and the percent 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 (Garrett & Sobel, 2003).

**Table 1**. Variable summary statistics.

| *Variable* | *N* | *Mean* | *Standard Deviation* | *Minimum* | *Maximum* |
|---|---|---|---|---|---|
| **Disaster variables** | | | | | |
| Federal disaster coverage | 1,102 | 27.49 | 308.62 | 0 | 8642.87 |
| Fatalities (persons) | 1,944 | 0.30 | 2.39 | 0 | 72.00 |
| Precipitation (inches) | 1,944 | 4.98 | 3.92 | 0 | 39.72 |
| Property damage (2019 USD) | 1,944 | 1.12e+8 | 1.25e+9 | 0 | 2.65e+10 |
| Property damage per capita (thousands 2019 USD) | 1,944 | 623.48 | 4227.2 | 0 | 8.27e+5 |
| Storm distance (kilometers) | 1,944 | 198.83 | 159.81 | 0.14 | 1164.61 |
| Total aid (2019 USD) | 1,944 | 2.71e+7 | 4.54e+8 | 0 | 1.95e+10 |
| Wind velocity (meters per second) | 1,944 | 15.18 | 7.76 | 0.53 | 53.07 |
| Year | 1,944 | 2012.61 | 3.35 | 2008 | 2017 |
| **County variables** | | | | | |
| Coastal (binary)* | 1,944 | 0.24 | 0.42 | 0 | 1.00 |
| FEMA region 1 (binary)* | 1,944 | 0.05 | 0.22 | 0 | 1.00 |
| FEMA region 2 (binary)* | 1,944 | 0.07 | 0.26 | 0 | 1.00 |
| FEMA region 3 (binary)* | 1,944 | 0.20 | 0.40 | 0 | 1.00 |
| FEMA region 4 (binary)* | 1,944 | 0.45 | 0.50 | 0 | 1.00 |
| FEMA region 6 (binary)* | 1,944 | 0.23 | 0.42 | 0 | 1.00 |
| Land area (square miles)* | 1,944 | 616.53 | 351.07 | 2 | 3361.48 |
| Median house age (years) | 1,944 | 34.14 | 9.61 | 12 | 73.00 |
| Median household income, log (2019 USD) | 1,944 | 10.84 | 0.29 | 10.06 | 11.84 |
| Number of previous PDDs with aid | 1,944 | 7.94 | 3.73 | 0 | 24.00 |
| Percentage of Democrat votes (%) | 1,944 | 41.93 | 16.21 | 8.43 | 92.46 |
| Percentage of land in floodplain (%)* | 1,944 | 22.60 | 21.14 | 0 | 100.00 |
| Percentage of mobile homes (%) | 1,944 | 16.38 | 11.24 | 0 | 57.99 |
| Percentage of racial minorities (%) | 1,944 | 27.54 | 18.34 | 0.18 | 86.27 |
| Percentage of renters (%) | 1,944 | 29.14 | 9.05 | 10.01 | 80.89 |
| Percentage of population 65+ (%) | 1,944 | 16.27 | 4.42 | 3.20 | 56.71 |
| Percentage receiving PA (%) | 1,944 | 2.15 | 1.26 | 0 | 13.72 |
| Swing county (binary) | 1,944 | 0.09 | 0.28 | 0 | 1.00 |
| Tax revenue per capita (thousands 2019 USD) | 1,944 | 1.40 | 1.81 | 0 | 37.16 |
| Total population, log | 1,944 | 10.87 | 1.38 | 5.48 | 15.35 |
| Unemployment rate (%) | 1,944 | 8.29 | 3.14 | 0 | 24.70 |
| Urban (binary)* | 1,944 | 0.53 | 0.50 | 0 | 1.00 |

Note: Variables with * are time-invariant by county

# 4 Methodology

**4.1 Stage 1**

In the first stage, we answer the question "What community and hazard characteristics are important predictors of counties that receive aid but that do not incur damage?" We do this by finding the correlates related to a county being in one of four categories: (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. Figure 6a is a scatterplot of total damage versus total aid for all county-PDD observations divided into the four categories. There are 422 county-PDDs that sustained no damage but that received aid, ranging from $1,243 to $1.18B (CPI adjusted to 2019 dollars). There are 193 county-PDDs that received no aid, but that sustain damage ranging from $208 to $4.15M (CPI adjusted to 2019 dollars). Figure 6b shows the spatial distribution of the categories from Figure 6a. 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 is in Appendix 2.

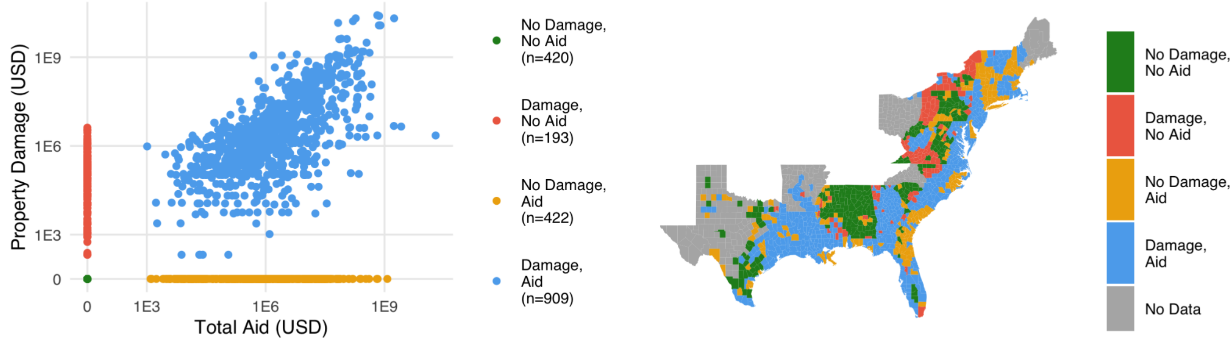


**Figure 6**. A scatterplot of sustained damage versus total aid for each county-PDD observation (**6a**). The spatial distribution of the scatterplot (**6b**). For counties with more than one observation, the mode is reported.

To address the research question, we fit the categorical data using a multinomial logistic regression model (Eq. 1). The dependent variables are county-PDD observations that have been binned into the four categories, $Y$. The reference category, $Y = k_O$, is assumed to be 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, $Y_{cp} = k_i, i = 1,2,3$, for county $c$ and PDD $p$. 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 $\varepsilon_{cp}$.

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

The model is estimated using the '*mlogit'* package in R (Croissant, 2020). 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 damage are omitted. Figure 7a shows the distribution of federal disaster coverage. Because of its heavy skew, Figure 7b shows this same distribution, except with federal disaster coverage logged. The majority of observations (70%) are less than or equal to one, and 61% have a federal disaster coverage less than 0.5. 11% of observations have a federal disaster coverage value greater than 10, meaning they received at least 10 times more aid than sustained damage. Figure 7c 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. Additional data discovery regarding how various independent variables relate with different quartiles of federal disaster coverage is presented in Appendix 3.

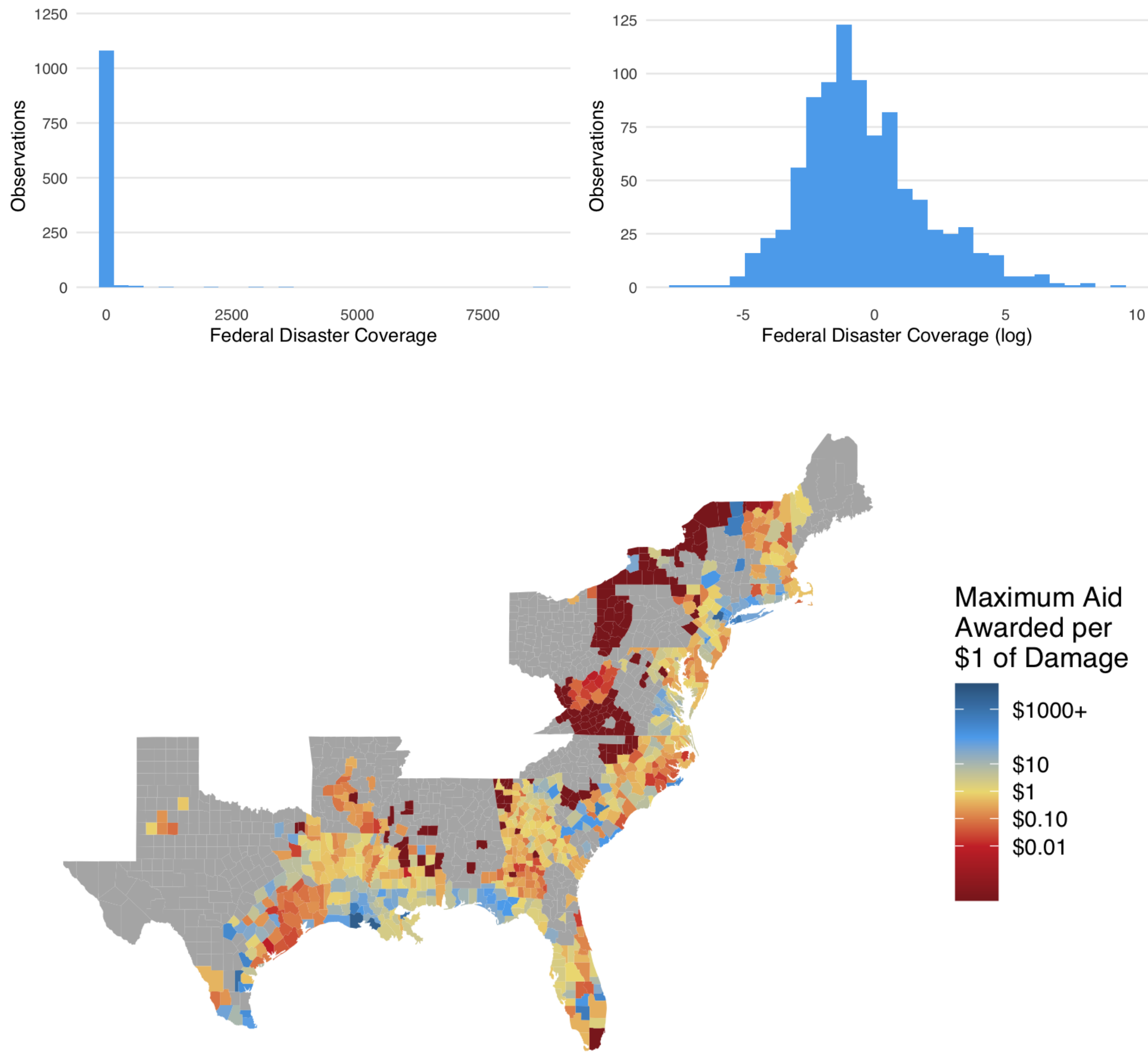


**Figure 7**. Histogram of the distribution of federal disaster coverage for observations with sustained damage (**7a**). Histogram of the distribution of federal disaster coverage, logged, for observations with sustained damage (**7b**). Note that observations with federal disaster coverage of zero (n = 193) are undefined when logged and omitted. The spatial distribution of the observations in the histogram (**7c**). In counties with more than one observation, the highest federal disaster coverage over all PDDs is shown.

To determine the correlates of higher and lower levels of federal disaster coverage, we fit all nonzero damage data using a multinomial logistic regression model (Eq. 2). The dependent variable is the binned quartile of the deviation of the county-PDD federal disaster coverage values ($y_{c_r p}$ for county $c$ in region $r$ and PDD $p$) from the median federal disaster coverage for its respective region ($\tilde{y}_r$ for region $r$). The four categories are: the 0-25th percentile of deviations (i.e., large negative deviations), the 25-50th percentile (i.e., moderate negative deviations), the 50-75th percentile (i.e., moderate positive deviations), and the 75-100th percentile (i.e., large positive deviations). The model is divided into three regions because of the variation of median federal disaster coverage across regions. The regions are: Northeast (states CT, DE, MD, ME, NH, NJ, NY, OH, PA, RI, VT), South Atlantic (states GA, NC, SC, VA, WV), and Gulf Coast (states AL, AR, FL, LA, MS, TX). We did not use FEMA regions due to singularity issues when fitting the model. The median federal disaster coverage rates of the Northeast, South Atlantic, and Gulf Coast regions are 0.272, 0.251, and 0.346, respectively. Additionally, we selected median instead of mean as our measure of central tendency because mean federal disaster coverage, due to the skew, would overinflate central estimates. Our reference category is the lowest quartile, the 0-25th percentile category, with lower and upper bounds $a_o$ and $b_o$, respectively. Using maximum likelihood estimation, the model estimates parameters that maximize the multinomial log-odds for the dependent variable's three alternative categories with lower and upper bounds $a_i$ and $b_i$, $i = 1,2,3$, respectively. The model is again 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 $\varepsilon_{cp}$.

$$ln\left(\frac{P(a_i \leq y_{c_r p} - \tilde{y}_r \leq b_i)}{P(a_o \leq y_{c_r p} - \tilde{y}_r \leq b_o)}\right) = \alpha + \beta H_{cp} + \gamma F_c + \delta D_{ct_p} + \zeta U_c + \varepsilon_{cp} \quad \text{(Eq. 2)}$$

The model is estimated using the '*mlogit'* package in R (Croissant, 2020). Model coefficients are exponentiated to produce the variables' relative risk ratios (RRR).

# 5 Results and Interpretation

## 5.1 Stage 1

The results of the multinomial logistic regression model for Stage 1 of our approach are included in Table 2. The reference category is *No Damage, Aid*.

**Table 2**. Results of Multinomial Logistic Regression for predicting damage and aid classification. The baseline category is *No Damage, Aid*. Parameters are reported as relative risk ratios (RRR).

| | *No Damage, No Aid* | *Damage, No Aid* | *Damage, Aid* |
|---|---|---|---|
| Intercept | 5.8e+08 (67.85 - 4.9e+15) * | 1.2e+09 (3.170 - 4.3e+17) * | 9.8e+06 (41.20 - 2.3e+12) * |
| **Disaster variables** | | | |
| Fatalities (persons) | 0.400 (0.115 - 1.386) | 0.403 (0.130 - 1.255) | 1.104 (1.004 - 1.214) * |
| Precipitation (inches) | 0.677 (0.623 - 0.735) *** | 0.966 (0.887 - 1.052) | 1.138 (1.091 - 1.187) *** |
| Storm distance (kilometers) | 0.999 (0.998 - 1.001) | 1.000 (0.998 - 1.002) | 1.000 (0.998 - 1.001) |
| Wind velocity (meters per second) | 0.917 (0.876 - 0.960) *** | 0.887 (0.837 - 0.940) *** | 1.036 (1.008 - 1.064) * |
| **County variables** | | | |
| Coastal (binary) | 0.210 (0.108 - 0.407) *** | 0.605 (0.317 - 1.156) | 1.002 (0.715 - 1.405) |
| FEMA region 2 (binary) | 1.677 (0.316 - 8.908) | 3.885 (1.127 - 13.39) * | 0.358 (0.178 - 0.719) ** |
| FEMA region 3 (binary) | 59.07 (11.52 - 302.9) *** | 30.71 (8.392 - 112.3) *** | 0.780 (0.369 - 1.652) |
| FEMA region 4 (binary) | 28.89 (4.802 - 173.8) *** | 5.640 (1.169 - 27.22) * | 0.661 (0.263 - 1.664) |
| FEMA region 6 (binary) | 7.342 (1.257 - 42.87) * | 1.680 (0.344 - 8.216) | 0.850 (0.346 - 2.088) |
| Land area (square miles) | 1.000 (1.000 - 1.001) | 0.999 (0.998 - 1.000) ** | 0.999 (0.999 - 1.000) *** |
| Median house age (years) | 1.012 (0.985 - 1.040) | 1.029 (0.998 - 1.060) | 0.980 (0.959 - 1.001) |
| Median household income, log (2019 USD) | 0.213 (0.055 - 0.835) * | 0.137 (0.026 - 0.728) * | 0.288 (0.100 - 0.833) * |
| Number of previous PDDs with aid | 1.027 (0.971 - 1.086) | 0.945 (0.885 - 1.009) | 0.975 (0.938 - 1.013) |
| Percentage of Democrat votes (%) | 1.029 (1.009 - 1.050) ** | 1.033 (1.009 - 1.059) ** | 1.011 (0.996 - 1.027) |
| Percentage of land in a floodplain (%) | 0.991 (0.980 - 1.003) | 1.006 (0.992 - 1.020) | 0.991 (0.984 - 0.999) * |
| Percentage of mobile homes (%) | 0.979 (0.954 - 1.004) | 0.976 (0.945 - 1.009) | 0.975 (0.957 - 0.994) * |
| Percentage of racial minorities (%) | 0.976 (0.959 - 0.994) ** | 0.969 (0.948 - 0.989) ** | 1.000 (0.986 - 1.014) |
| Percentage of renters (%) | 0.949 (0.923 - 0.976) *** | 0.943 (0.911 - 0.977) ** | 0.947 (0.927 - 0.968) *** |
| Percentage of population 65+ (%) | 0.943 (0.892 - 0.997) * | 0.992 (0.934 - 1.054) | 0.987 (0.950 - 1.024) |
| Percentage receiving PA (%) | 0.953 (0.822 - 1.104) | 1.068 (0.902 - 1.265) | 0.978 (0.869 - 1.101) |
| Swing county (binary) | 1.146 (0.627 - 2.092) | 0.743 (0.367 - 1.508) | 1.061 (0.677 - 1.661) |
| Tax revenue per capita (thousands 2019 USD) | 1.127 (1.004 - 1.266) * | 0.681 (0.511 - 0.909) ** | 1.057 (0.976 - 1.145) |
| Total population, log | 0.835 (0.673 - 1.036) | 1.258 (0.973 - 1.626) | 1.080 (0.918 - 1.271) |
| Unemployment rate (%) | 0.982 (0.917 - 1.051) | 0.897 (0.820 - 0.982) * | 0.976 (0.925 - 1.030) |
| Urban (binary) | 1.207 (0.790 - 1.845) | 1.329 (0.798 - 2.214) | 0.962 (0.682 - 1.358) |
| ***P-value of model*** | ***2.15e-222*** | | |

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

The model has several statistically significant hazard intensity indicators. For example, the statistically significant RRR value of fatalities for the *Damage, Aid* category indicates that for every additional fatality, an observation is 1.104 times as likely (i.e., more likely) to be categorized in the *Damage, Aid* category relative to the reference category, *No Damage, Aid*. Similarly, as precipitation increases by 1 inch, an observation is 0.677 times as likely (i.e., less likely) to be categorized in the *No Damage, No Aid* category, and 1.138 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 0.917 and 0.887 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*.

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 (0.210 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 0.991 times as likely (i.e., less likely) to be categorized in the *Damage, Aid* category than the reference category, *No Damage, Aid*.

Many social vulnerability variables and county capacity variables are statistically significant in our model. The percentage of mobile homes, the percentage of racial minorities, the percentage of renters, the percentage of the population that is 65+, and unemployment rate have statistically significant RRR's across all three alternative categories: *No Damage, No Aid*; *Damage, No Aid*; and *Damage, Aid*. Interestingly, all of these variables have RRR's less than 1, indicating that as these variables increase (i.e., as the region becomes more socially-vulnerable), there is a decreased likelihood of being categorized into any of the alternative categories relative to our reference category of *No Damage, Aid*. More specifically, as social vulnerability increases, a county is more likely to be in the reference category, *No Damage, Aid*. Variables reflecting county wealth and capacity, specifically median household income and tax revenue, suggest the opposite. As median household income increases, counties are more likely to be in the reference category, *No Damage, Aid*, than the other categories. Similarly, as tax revenue increases by $1,000 per capita, an observation is 1.127 times as likely (i.e., more likely) to be categorized as *No Damage, No Aid* than the reference category, *No Damage, Aid*. Conversely, as tax revenue increases by $1,000 per capita, an observation is 0.681 times as likely (i.e., less likely) to be categorized as *Damage, No Aid, t*han the reference category *No Damage, Aid*.

Finally, our results indicate that damage and aid categorization are significantly impacted by FEMA region and political leaning. All FEMA region variables contain statistically significant RRR's for the alternative categories. Many RRR's are well above 1, meaning in this case, that observations in FEMA Regions 3, 4, and 6 are more likely to be in the category *No Damage, No Aid* than the reference category of *No Damage, Aid*. Similarly, FEMA Regions 2, 3, and 4 are more likely to be in the category *Damage, No Aid* than the reference category of *No Damage, Aid.* Finally, an observation in FEMA Region 2 is 0.358 times as likely (i.e., less likely) to fall in the *Damage, Aid* category as the *No Damage, Aid* category. Additionally, our statistically significant percentage of Democrat votes RRR's indicate that a 1% increase in Democrat votes in the previous presidential election renders an observation 1.029 and 1.033 times as likely (i.e., more likely) to fall in the *No Damage, No Aid* and *Damage, No Aid* categories, respectively, compared to our reference category, *No Damage, Aid*.

### 5.2 Stage 2

The results of the multinomial logistic regression model for Stage 2 are presented in Table 3. The reference category is the lowest quantile, Quantile 1 (0-25th percentile), meaning the quartile of observations with federal disaster coverage values furthest below the respective regional medians.

**Table 3.** Results of Multinomial Logistic Regression for predicting the quantile of federal disaster coverage deviation from the regional median. Baseline category is Quantile 1 (0-25th percentile). Tabulated values are relative risk ratios (RRR).

| | *Quantile 2 (25-50%)* | *Quantile 3 (50-75%)* | *Quantile 4 (75-100%)* |
|---|---|---|---|
| Intercept | 31.95 (1.5e-06 - 6.6e+08) | 2.3e-03 (4.5e-11 - 1.2e+05) | 7.6e-06 (1.3e-13 - 433.0) |
| **Disaster variables** | | | |
| Fatalities (persons) | 0.992 (0.936 - 1.051) | 0.961 (0.845 - 1.094) | 1.143 (1.017 - 1.286) * |
| Precipitation (inches) | 1.087 (1.037 - 1.140) *** | 1.055 (0.998 - 1.116) | 1.035 (0.975 - 1.097) |
| Prop. damage per cap. (thousands 2019 USD) | 0.943 (0.913 - 0.975) *** | 0.708 (0.589 - 0.852) *** | 0.039 (0.014 - 0.113) *** |
| Storm distance (kilometers) | 0.997 (0.994 - 0.999) ** | 0.997 (0.995 - 1.000) * | 1.002 (1.000 - 1.004) * |
| Wind velocity (meters per second) | 1.040 (0.998 - 1.083) | 1.042 (0.996 - 1.090) | 1.148 (1.095 - 1.203) *** |
| **County variables** | | | |
| Coastal (binary) | 2.576 (1.477 - 4.494) *** | 1.694 (0.952 - 3.012) | 2.278 (1.291 - 4.022) ** |
| Land area (square miles) | 1.000 (0.999 - 1.001) | 1.001 (1.000 - 1.001) | 1.000 (0.999 - 1.001) |
| Median house age (years) | 0.947 (0.919 - 0.977) *** | 0.932 (0.903 - 0.963) *** | 0.973 (0.943 - 1.004) |
| Median household income, log (2019 USD) | 0.793 (0.184 - 3.409) | 1.515 (0.322 - 7.135) | 2.255 (0.483 - 10.54) |
| Number of previous PDDs with aid | 0.977 (0.920 - 1.037) | 0.961 (0.903 - 1.021) | 1.004 (0.945 - 1.067) |
| Percentage of Democrat votes (%) | 1.003 (0.984 - 1.023) | 0.981 (0.960 - 1.002) | 0.983 (0.962 - 1.004) |
| Percentage of land in a floodplain (%) | 0.994 (0.983 - 1.006) | 1.001 (0.989 - 1.013) | 1.003 (0.991 - 1.015) |
| Percentage of mobile homes (%) | 1.028 (0.997 - 1.061) | 1.036 (1.004 - 1.070) * | 1.045 (1.011 - 1.080) ** |
| Percentage of racial minorities (%) | 1.002 (0.985 - 1.019) | 1.039 (1.019 - 1.059) *** | 1.019 (0.999 - 1.039) |
| Percentage of renters (%) | 1.025 (0.991 - 1.060) | 1.036 (1.000 - 1.073) | 1.010 (0.975 - 1.045) |
| Percentage of population 65+ (%) | 0.996 (0.948 - 1.047) | 1.034 (0.984 - 1.086) | 0.974 (0.925 - 1.027) |
| Percentage receiving PA (%) | 0.779 (0.647 - 0.937) ** | 0.776 (0.641 - 0.939) ** | 1.009 (0.847 - 1.202) |
| Region Northeast (binary) | 6.131 (2.318 - 16.22) *** | 14.10 (5.091 - 39.06) *** | 1.553 (0.551 - 4.379) |
| Region South Atlantic (binary) | 2.230 (1.232 - 4.035) ** | 2.423 (1.325 - 4.431) ** | 1.561 (0.855 - 2.852) |
| Swing county (binary) | 1.049 (0.545 - 2.017) | 0.952 (0.488 - 1.857) | 0.725 (0.355 - 1.481) |
| Tax revenue per capita (thousands 2019 USD) | 1.638 (1.227 - 2.186) *** | 1.664 (1.238 - 2.238) *** | 1.803 (1.351 - 2.406) *** |
| Total population, log | 0.798 (0.624 - 1.020) | 0.972 (0.753 - 1.255) | 0.955 (0.746 - 1.224) |
| Unemployment rate (%) | 1.110 (1.021 - 1.207) * | 1.064 (0.976 - 1.160) | 1.035 (0.946 - 1.133) |
| Urban (binary) | 1.035 (0.629 - 1.703) | 0.864 (0.516 - 1.448) | 1.170 (0.695 - 1.968) |
| ***P-value of model*** | ***2.71e-61*** | | |

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

Several of the hazard intensity and hazard exposure indicators in this model are statistically significant. For example, the RRR of the precipitation variable for Quantile 2 indicates that for a 1-inch increase in precipitation, an observation is 1.087 times as likely (i.e., 0.087 or 8.7% more likely) to fall within Quantile 2 compared to Quantile 1. This means that as precipitation increases, observations are more likely to have higher federal disaster coverage. Similarly, for every additional fatality or 1-m/s increase in maximum sustained wind velocity, an observation is 1.143 times and 1.148 times, respectively, as likely to fall into Quantile 4 compared to Quantile 1. The storm distance variable RRR values for Quantile 2 and Quantile 3 - both 0.997 - indicate that an observation is less likely to fall within these quantiles relative to Quantile 1 as minimum storm distance increases. This tells us that counties with closer proximities to these hurricanes have a higher probability of falling within higher federal disaster coverage brackets. Similarly, the RRR's for our coastal county variable - 2.576 for Quantile 2 and 2.278 for Quantile 4 - indicate that coastal counties are over twice as likely to fall into higher federal disaster coverage brackets. In aggregate, the model results show that greater hazard intensity and greater hazard exposure increase an observation's likelihood of falling within a higher federal disaster coverage bracket.

The property damage per capita variable has statistically significant RRR's for all three alternative quantiles. The RRR's - 0.943 for Quantile 2, 0.708 for Quantile 3, and 0.039 for Quantile 4 - indicate that as property damage per capita increases, an observation's likelihood of falling within a higher federal disaster coverage bracket progressively decreases. In other words, for every $1000 increase in per capita damage, the likelihood of falling within Quantile 3 is roughly 1.5 times less than the likelihood of falling within Quantile 1, and the likelihood of falling within Quantile 4 is just 1/25th of the likelihood of falling within Quantile 1.

The findings from our statistically significant social vulnerability and local capacity variables are mixed. Several variables suggest that increased social vulnerability increases the likelihood of falling into a higher federal disaster coverage bracket. For example, the percentage of mobile homes, the percentage of racial minorities, and unemployment rate have RRR's greater than 1 for Quantiles 2, 3, and 4. These RRR's indicate that as these variables increase, so does the likelihood of falling within these higher federal disaster coverage quantiles. As any of these variables increase, social vulnerability increases. Thus, this suggests that increased social vulnerability correlates with higher levels of federal disaster coverage.

Other social vulnerability and local capacity variables, however, suggest the opposite. Regarding infrastructure, the statistically significant RRR's for the median house age variable indicate that as house age increases by one year, an observation is 0.947 times and 0.932 times as likely to fall within Quantile 2 and Quantile 3, respectively. In other words, older residential infrastructure decreases the likelihood of falling within higher federal disaster coverage brackets. Regarding wealth, the RRR's for the percentage of households receiving public assistance - 0.779 for Quantile 2 and 0.776 for Quantile 3 - indicate that as the percentage of households receiving public assistance increases, the likelihood of falling within higher federal disaster coverage quantiles decreases. Similarly, the RRR's of tax revenue - 1.638 for Quantile 2, 1.664 for Quantile 3, and 1.803 for Quantile 4 - indicate that counties with higher tax revenue, and thus higher local capacity, are much more likely to fall within a higher federal disaster coverage bracket compared to Quantile 1.

Finally, the model results indicate that an observation's likely federal disaster coverage quantile is greatly impacted by the observation's region. The RRR's of the Northeast region variable indicate that observations in this region, relative to the Gulf Coast region, are over 6 times more likely to be in Quantile 2 and over 14 times more likely to be in Quantile 3 compared to Quantile 1. Similarly, observations are over twice as likely to fall within these quantiles if they are from the Southeast region compared to the Gulf Coast region. There are no statistically significant results of region variables for Quantile 4, suggesting that observations in the highest bracket of federal disaster coverage are not significantly regionally-dependent.

# 6 Discussion

## 6.1 Stage 1

Regarding hazard intensity and hazard exposure, our results suggest three main findings. First, greater storm intensity, as measured by fatalities, 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 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 assuming 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 (Grube et al., 2018); on the other hand, we would not expect greater hazard intensity to result in less damage (Elsner et al., 2011; Knighton et al., 2020).

Third, greater hazard exposure, as measured by the coastal county indicator and the percentage of land in a floodplain, decreases the likelihood of falling into alternative categories relative to the *No Damage, Aid* case. Interestingly, this finding indicates that observations in the *No Damage, Aid* category are more exposed to flooding, supplementing the previous finding that observations in the *No Damage, Aid* category also experience more severe storm conditions than counties that do not receive aid (regardless of damage), although these conditions are less severe than those experienced by counties that both receive aid and have reported damages. One possible explanation is that observations in the *No Damage, Aid* category are, in reality, experiencing storm damage and receiving aid for said damage, but the damage is underreported.

These damages may be less than those in the *Damage, Aid* category because observations in *No Damage, Aid* category appear to experience lower storm intensity than observations that receive aid and have reported damages. Lower levels of damage may be a potential driver for this reporting error. A second possible explanation is that these counties are, in fact, receiving federal disaster aid despite sustaining no damage. We see both of these explanations anecdotally in our data. For instance, Chatham County, GA sustained over $30 million in damage following Hurricane Matthew in 2016, yet had no reported damage in the SHELDUS dataset (Coleman, 2017). Conversely, Coryell County, TX received millions of dollars in aid following Hurricane Harvey in 2017 despite sustaining no damage (Despart, 2022).

Our results related to social vulnerability and local capacity variables suggest two main findings. First, our variables that capture the percentage of mobile homes, the percentage of racial minorities, the percentage of renters, the percentage of the population that is 65+, and unemployment rate all indicate that as social vulnerability increases, the likelihood of an observation falling into an alternative category decreases. This indicates that observations in the *No Damage, Aid* category may be disproportionately vulnerable to disaster damages and have fewer internal resources to recover. In this case, these areas are receiving federal aid for incurred disaster damage, but may be overlooked in disaster loss datasets. As these 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 risk and exposure to disasters that these areas face.

The second main finding is that some variables indicating county wealth - namely, median household income and tax revenue per capita - indicate that as wealth increases, the likelihood of an observation falling into an alternative category decreases. 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 (Peacock & Girard, 1997). 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.

### 6.2 Stage 2

Our Stage 2 model demonstrates that as hazard intensity and hazard exposure increase, the likelihood of receiving higher federal disaster coverage increases. This trend may have several explanations. First, higher-intensity storms receive more media coverage, which has been shown to pressure local politicians and drive local administrators to procure disaster aid (Eisensee & Strömberg, 2007). It is also possible that areas more exposed to hazards may be more prepared to apply for and navigate federal disaster aid grants. For example, these areas may already have internal administrative procedures and resources in place, either due to past disaster experience or simply due to heightened risk. Areas more exposed to hazards may also have hardened infrastructure and other mitigation measures in place, decreasing damage and thus inherently increasing federal disaster coverage. Finally, as previously mentioned, poorer populations with fewer assets are more likely to live in areas exposed to hazards (Arcaya et al., 2020; Atreya et al., 2015; Hendricks & Van Zandt, 2021; Ueland & Warf, 2006). The reduced potential for damage rendered by having fewer assets inherently increases federal disaster coverage if aid is held constant. However, the plausibility of some of these explanations is likely location-specific and highly dependent on a county's local capacity. The reduced political voice, administrative capacity, and resources for mitigation of counties with greater social vulnerability and lower local capacity would weaken explanations 1-3, respectively (Aylett, 2014; Dixon et al., 2017; Polacko, 2022).

We also find that greater damage per capita progressively - and, for higher quantiles, significantly - decreases an observation's likelihood of being in a higher federal disaster coverage bracket. This may be indicative of the costliest disasters being difficult to fully reimburse compared to less expensive, smaller-scale disasters. Alternatively, it is possible that areas with smaller populations (and therefore, larger damages per capita) receive less federal aid than more populated areas receiving equal damage. This could be a result of the majority of federal disaster aid allocations targeting public infrastructure - of which there is generally more in populous and urban counties - in the form of PA grants (OpenFEMA, 2021b, 2021a; HUD, 2021). This could also stem from issues pertaining to reduced local capacity in less populous counties and subsequent barriers in applying for federal assistance (Domingue & Emrich, 2019).

Our findings from the statistically significant social vulnerability and local capacity indicators are mixed. An increase in some variables - namely, the proportion of the population that is nonwhite, the proportion of mobile homes, and unemployment rate - is associated with a greater likelihood of being in a higher federal disaster coverage bracket. This may be due to the federal aid programs' focus on the underinsured and on underprivileged communities (FEMA, 2023c). Conversely, an increase in local tax revenue, median house age, and the proportion of the county receiving public assistance suggest that greater local capacity increases the likelihood of being in a higher federal disaster coverage bracket. This could be reflective of counties with greater local capacity having more administrative assets to successfully navigate the federal aid process (Howell & Elliott, 2019).

Finally, we find that region is a statistically significant indicator of federal disaster coverage. The Northeast and South Atlantic regions are more likely to receive higher federal disaster coverage than the Gulf Coast, with the Northeast being the most likely to receive higher federal disaster coverage. These trends may represent administrative, disaster experience, and infrastructure differences among counties during disaster response and application for federal aid.

# 7 Conclusion

In this research, we develop multinomial logistic regression models to explore the effects of various county and disaster characteristics on the proportion of damages that are restituted by federal disaster aid, or federal disaster coverage. Specifically, we evaluate the influence of factors such as county demographics, local capacity indicators, and hazard intensity metrics previously explored in the literature on (1) the likelihood of a county receiving federal disaster aid but not sustaining any damage, and (2) the level of federal disaster coverage received by counties that reported damage. We include records from 14 hurricanes that hit the continental U.S. between 2008 and 2017 and limit our analysis to the three largest grant providers of disaster recovery funds: FEMA PA, FEMA IHP, and HUD CDBG-DR. Unlike previous work, this is the first study, to our knowledge, that explores salient factors for the ratio of awarded aid to incurred damage, as opposed to aid or damage individually. We argue that considering this fraction provides necessary context to understand how much of the burden of recovery is actually relieved through federal disaster aid and how much is still left to communities to self-fund, and is thereby more reflective of the pragmatic impact of federal aid at the county-level and its implications for realistic recovery.

Results from Stage 1 of our analysis show that observations that receive aid but have no reported damage experience greater storm intensity and more exposure than observations that do not receive aid, and these observations exhibit mixed social vulnerability and local capacity compared to the other categories of observations. We acknowledge that 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. Our findings regarding social vulnerability and local capacity indicators were mixed, with most trends suggesting that greater social vulnerability increases the likelihood of falling into the Damage, No Aid category. This may suggest that areas of high social vulnerability are disproportionately underreported in NWS's data collection for the Storm Data and SHELDUS datasets. This pattern would introduce difficulties and pose equity concerns when attempting to evaluate the trends and correlates of federal disaster coverage.

Stage 2 of our analysis demonstrates that federal disaster coverage increases with increased storm intensity and hazard exposure. The results also indicate that federal disaster coverage decreases as per capita damage increases, suggesting perhaps the costliest disasters are most difficult to reimburse, or that less populous areas receive lower levels of federal disaster coverage despite having otherwise equivalent damage. This may reflect either the predominance of federal disaster aid grants aimed toward public infrastructure recovery, or the difficulties that areas with lower local capacities have when meeting cost-share requirements or otherwise navigating the disaster aid process. Our findings regarding social vulnerability indicators were mixed. Some variables show that greater social vulnerability increases the likelihood of receiving higher federal disaster coverage, while others show a decrease. We find that greater local capacity consistently increases the likelihood of receiving higher federal disaster coverage.

This work can be further expanded. First, additional damage data can be collected to either supplement or replace current SHELDUS damage estimates. For example, damage estimates from FEMA Preliminary Damage Assessment Reports could be used to replace the models' current damage estimates. While these estimates may be more biased than third-party damage estimates, findings could still reveal patterns between damage reported to FEMA and ultimate FEMA aid allotment. Because areas that received aid but had no reported damage (and were suspected to be missing data) were predominantly socially vulnerable, additional damage estimates for these areas may change the findings for Stage 2 of our analysis.

Overall, our findings suggest some level of disparities in disaster loss reporting and 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 outcomes.

# Appendix 1 Model results excluding CDBR-DR data

**Table 4**. Results of Multinomial Logistic Regression for predicting damage and aid classification omitting CDBG-DR data. The baseline category is *No Damage, Aid*. Parameters are reported as relative risk ratios (RRR).

| | *No Damage, No Aid* | *Damage, No Aid* | *Damage, Aid* |
|---|---|---|---|
| Intercept | 1.0e+06 (0.074 - 1.4e+13) | 2.4e+08 (0.600 - 9.4e+16) | 7.5e+05 (1.777 - 3.2e+11) * |
| **Disaster variables** | | | |
| Fatalities (persons) | 0.282 (0.079 - 1.008) | 0.308 (0.096 - 0.983) * | 1.096 (0.998 - 1.203) |
| Precipitation (inches) | 0.623 (0.574 - 0.677) *** | 0.896 (0.825 - 0.973) ** | 1.100 (1.054 - 1.148) *** |
| Storm distance (kilometers) | 0.999 (0.997 - 1.000) | 1.000 (0.998 - 1.002) | 1.000 (0.998 - 1.001) |
| Wind velocity (meters per second) | 0.889 (0.850 - 0.930) *** | 0.879 (0.831 - 0.929) *** | 1.026 (0.997 - 1.056) |
| **County variables** | | | |
| Coastal (binary) | 0.299 (0.164 - 0.544) *** | 0.574 (0.306 - 1.078) | 1.024 (0.721 - 1.455) |
| FEMA region 2 (binary) | 6.691 (1.575 - 28.42) * | 7.007 (2.291 - 21.43) *** | 0.448 (0.213 - 0.944) * |
| FEMA region 3 (binary) | 61.93 (14.79 - 259.3) *** | 22.35 (6.955 - 71.82) *** | 0.984 (0.454 - 2.133) |
| FEMA region 4 (binary) | 29.65 (5.887 - 149.3) *** | 3.706 (0.847 - 16.21) | 0.927 (0.352 - 2.445) |
| FEMA region 6 (binary) | 22.14 (4.493 - 109.1) *** | 3.456 (0.797 - 14.99) | 1.587 (0.608 - 4.146) |
| Land area (square miles) | 1.000 (0.999 - 1.000) | 0.999 (0.998 - 1.000) ** | 0.999 (0.999 - 0.999) *** |
| Median house age (years) | 0.995 (0.968 - 1.023) | 1.003 (0.974 - 1.034) | 0.971 (0.950 - 0.993) * |
| Median household income, log (2019 USD) | 0.347 (0.085 - 1.420) | 0.146 (0.027 - 0.791) * | 0.360 (0.118 - 1.095) |
| Number of previous PDDs with aid | 1.034 (0.979 - 1.093) | 0.955 (0.896 - 1.017) | 0.981 (0.942 - 1.021) |
| Percentage of Democrat votes (%) | 1.043 (1.021 - 1.065) *** | 1.043 (1.018 - 1.069) *** | 1.020 (1.003 - 1.037) * |
| Percentage of land in a floodplain (%) | 0.989 (0.978 - 1.000) * | 0.999 (0.985 - 1.013) | 0.990 (0.983 - 0.998) * |
| Percentage of mobile homes (%) | 0.997 (0.971 - 1.023) | 0.989 (0.957 - 1.022) | 0.981 (0.962 - 1.001) |
| Percentage of racial minorities (%) | 0.965 (0.947 - 0.984) *** | 0.962 (0.942 - 0.983) *** | 0.993 (0.978 - 1.008) |
| Percentage of renters (%) | 0.968 (0.941 - 0.996) * | 0.958 (0.926 - 0.991) * | 0.952 (0.931 - 0.974) *** |
| Percentage of population 65+ (%) | 0.953 (0.901 - 1.007) | 1.014 (0.956 - 1.075) | 0.985 (0.948 - 1.024) |
| Percentage receiving PA (%) | 0.956 (0.827 - 1.107) | 1.113 (0.942 - 1.314) | 0.958 (0.846 - 1.084) |
| Swing county (binary) | 1.471 (0.784 - 2.760) | 0.833 (0.400 - 1.737) | 1.219 (0.749 - 1.984) |
| Tax revenue per capita (thousands 2019 USD) | 1.116 (0.993 - 1.256) | 0.719 (0.549 - 0.941) * | 1.055 (0.971 - 1.146) |
| Total population, log | 0.922 (0.741 - 1.147) | 1.400 (1.087 - 1.804) ** | 1.087 (0.916 - 1.289) |
| Unemployment rate (%) | 1.026 (0.956 - 1.101) | 0.920 (0.840 - 1.008) | 0.999 (0.944 - 1.057) |
| Urban (binary) | 1.114 (0.720 - 1.725) | 1.260 (0.752 - 2.110) | 0.934 (0.650 - 1.341) |
| ***P-value of model*** | ***4.23e-236*** | | |

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

**Table 5**. Results of Multinomial Logistic Regression for predicting the quantile of federal disaster coverage deviation from the regional median omitting CDBG-DR data. Baseline category is Quantile 1 (0-25th percentile). Tabulated values are relative risk ratios (RRR).

| | ***Quantile 2 (25-50%)*** | ***Quantile 3 (50-75%)*** | ***Quantile 4 (75-100%)*** |
|---|---|---|---|
| Intercept | 403.5 (9.5e-06 - 1.7e+10) | 0.032 (7.1e-10 - 1.4e+06) | 2.1e+04 (2.4e-04 - 1.9e+12) |
| **Disaster variables** | | | |
| Fatalities (persons) | 1.086 (0.951 - 1.240) | 1.055 (0.909 - 1.224) | 1.364 (1.121 - 1.659) ** |
| Precipitation (inches) | 1.056 (1.008 - 1.107) * | 1.050 (0.993 - 1.111) | 1.086 (1.022 - 1.153) ** |
| Prop. damage per cap. (thousands 2019 USD) | 0.935 (0.902 - 0.970) *** | 0.676 (0.555 - 0.822) *** | 1.7e-03 (2.5e-04 - 0.012) *** |
| Storm distance (kilometers) | 0.997 (0.995 - 1.000) * | 0.996 (0.993 - 0.998) *** | 1.002 (1.000 - 1.004) |
| Wind velocity (meters per second) | 1.051 (1.010 - 1.094) * | 1.020 (0.976 - 1.066) | 1.162 (1.106 - 1.221) *** |
| **County variables** | | | |
| Coastal (binary) | 1.711 (0.977 - 2.995) | 2.011 (1.150 - 3.516) * | 1.605 (0.903 - 2.851) |
| Land area (square miles) | 1.000 (0.999 - 1.001) | 1.000 (1.000 - 1.001) | 1.000 (0.999 - 1.001) |
| Median house age (years) | 0.982 (0.950 - 1.015) | 0.943 (0.911 - 0.976) *** | 0.960 (0.927 - 0.993) * |
| Median household income, log (2019 USD) | 0.639 (0.140 - 2.915) | 1.307 (0.286 - 5.977) | 0.298 (0.061 - 1.448) |
| Number of previous PDDs with aid | 0.967 (0.908 - 1.029) | 0.957 (0.898 - 1.021) | 0.982 (0.918 - 1.051) |
| Percentage of Democrat votes (%) | 0.982 (0.961 - 1.003) | 0.984 (0.964 - 1.006) | 0.958 (0.936 - 0.980) *** |
| Percentage of land in a floodplain (%) | 0.997 (0.985 - 1.008) | 0.999 (0.987 - 1.010) | 1.002 (0.989 - 1.014) |
| Percentage of mobile homes (%) | 1.003 (0.971 - 1.036) | 1.034 (1.003 - 1.067) * | 1.012 (0.979 - 1.046) |
| Percentage of racial minorities (%) | 1.015 (0.997 - 1.034) | 1.035 (1.015 - 1.054) *** | 1.037 (1.017 - 1.058) *** |
| Percentage of renters (%) | 1.030 (0.994 - 1.066) | 1.046 (1.010 - 1.083) * | 1.011 (0.976 - 1.047) |
| Percentage of population 65+ (%) | 1.026 (0.976 - 1.079) | 1.035 (0.985 - 1.088) | 0.990 (0.940 - 1.042) |
| Percentage receiving PA (%) | 0.799 (0.663 - 0.964) * | 0.810 (0.675 - 0.971) * | 0.828 (0.689 - 0.994) * |
| Region Northeast (binary) | 66.23 (20.80 - 210.9) *** | 61.53 (19.06 - 198.6) *** | 25.81 (7.648 - 87.10) *** |
| Region South Atlantic (binary) | 0.588 (0.321 - 1.080) | 0.772 (0.430 - 1.387) | 1.200 (0.658 - 2.189) |
| Swing county (binary) | 1.923 (0.931 - 3.971) | 1.586 (0.765 - 3.288) | 1.067 (0.490 - 2.323) |
| Tax revenue per capita (thousands 2019 USD) | 1.073 (0.800 - 1.438) | 1.263 (0.947 - 1.684) | 1.604 (1.199 - 2.145) ** |
| Total population, log | 0.831 (0.641 - 1.077) | 0.981 (0.756 - 1.272) | 1.173 (0.902 - 1.525) |
| Unemployment rate (%) | 0.984 (0.904 - 1.071) | 1.005 (0.925 - 1.091) | 0.980 (0.898 - 1.070) |
| Urban (binary) | 1.081 (0.648 - 1.804) | 0.976 (0.586 - 1.624) | 1.161 (0.688 - 1.958) |
| ***P-value of model*** | ***1.73e-81*** | | |

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

# Appendix 2 Data discovery for Stage 1

Figures 8a-f show box-and-whisker distributions of storm intensity variables, as well as variables that indicate disaster aid experience, exposure, and capacity, separated by category. We find that observations with more aid and with more damage experience more intense storms. The distributions also show that observations that do not receive aid have less experience receiving federal funds for past PDDs compared to observations that did receive aid. Observations that received aid are also more vulnerable to flooding and more populous - reflecting both increased hazard exposure and capacity - compared to those that did not receive aid. Across these variables, the distributions of observations in the *No Damage, Aid* category and of observations in the *Damage, Aid* category are very similar, with the former experiencing slightly less intense storms.

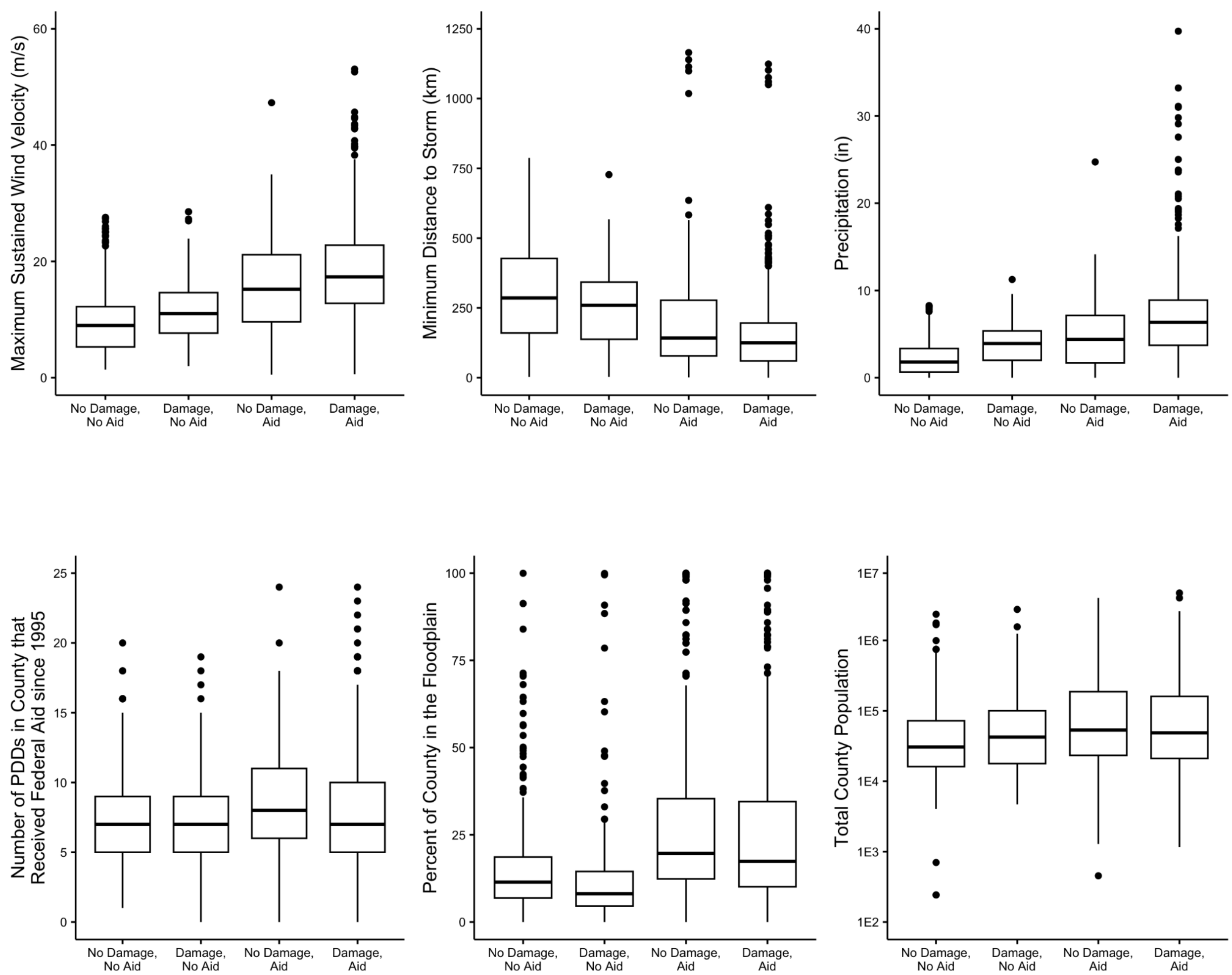


**Figure 8**. Box-and-whisker plots showing the distribution of a. maximum sustained wind velocity, b. minimum storm distance, c. precipitation, d. number of PDDs for which the county previously received federal aid, e. proportion of the county that is in a floodplain, and f. total county population by category. T-statistics and statistical significance (p-value <= 0.05, indicated with an asterisk) are also noted.

# Appendix 3 Data discovery for Stage 2

Figures 9a-e show the distribution of variables reflecting hazard intensity, social vulnerability, and property damage per capita by federal disaster coverage quantile, and Figure 9f shows the distribution of federal disaster coverage by FEMA region. Overall, storms appear less intense in the lowest quantile of federal disaster coverage. Storm intensity trends remain ambiguous as federal disaster coverage increases. Federal disaster coverage appears to increase as minority populations increase, indicating that federal aid disbursement relative to damage may prioritize the socially vulnerable. However, federal disaster coverage also appears to decrease as property damage per capita increases, which may be indicative of costlier disasters or less populous regions receiving less federal disaster coverage. We also find that some FEMA regions - particularly FEMA regions 1 and 3 - receive lower levels of federal disaster coverage compared to other regions, which may be a product of the region's wealth, infrastructure, exposure, or administrative differences.

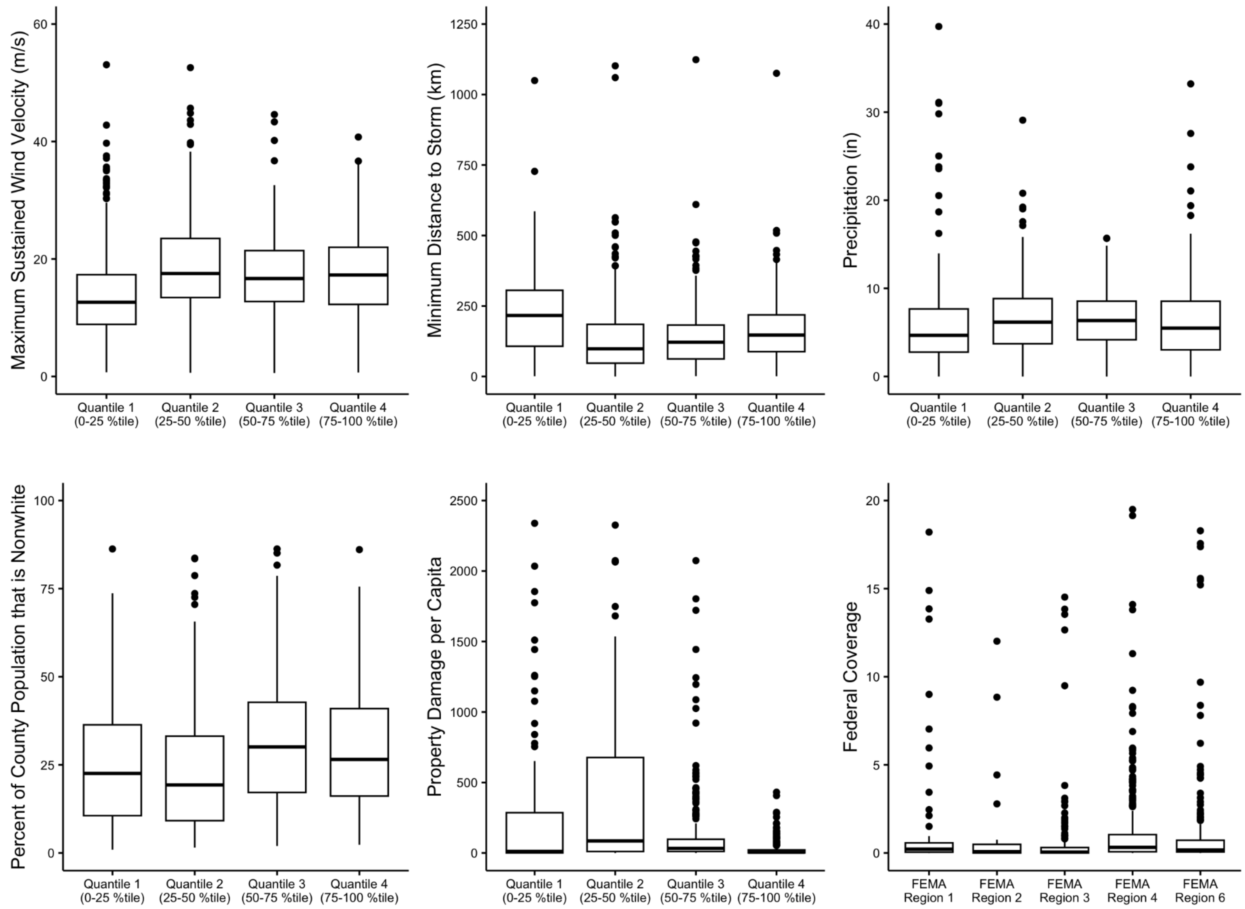


**Figure 9**. Box-and-whisker plots showing the distribution of a. maximum sustained wind velocity, b. minimum storm distance, c. precipitation, d. Proportion of the county population that is nonwhite, and e. Property damage per capita by federal disaster coverage quantile, and f. Federal disaster coverage by FEMA region. T-statistics and statistical significance (p-value <= 0.05, indicated with an asterisk) are also noted.

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