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Losses from Natural Disasters: County-Level Data on Damages, Injuries, and Fatalities

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Abstract

We introduce the first comprehensive publicly available dataset on county-level damages, injuries, and fatalities from natural disasters in the U.S. and present a few facts on the economic and human costs of extreme climate events. Our source is the National Oceanic and Atmospheric Administration's Storm Events Database, which reports losses for geographic areas largely defined based on meteorological science. We map these areas to counties using geographic tools together with the spatial distribution of population, housing stock, and economic activity. Our estimates are particularly accurate for severe disasters. The Losses from Natural Disasters dataset is regularly updated at https://newyorkfed.org/research/policy/natural-disaster-losses.

JEL classification: H12, H71, Q54
Key words: natural disasters, physical risk

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1 Introduction

Natural disasters generate substantial costs for households, firms, and governments. Businesses monitor their exposure to physical risks, homeowners face rising insurance premiums, and the mounting costs of disaster response often strain public budgets. However, somewhat surprisingly, empirical analyses of the economic and human costs of natural disasters are currently hindered by data limitations. The National Oceanic and Atmospheric Administration (NOAA) collects official data on damages, injuries, and fatalities, but nearly 40% of these estimates are reported for meteorological "zones"—geographic units that might span many counties (e.g., a valley intersecting three counties) or include only parts of one (e.g., the coastal portion of one county), making it difficult to merge losses from NOAA with standard administrative datasets.

In this paper, we introduce *Losses from Natural Disasters*—new and comprehensive data on county-level damages, injuries, and fatalities from natural disasters in the U.S. from 1996 to the present. Using geographic tools together with weighting schemes based on the spatial distribution of population, housing stock, and economic activity, we apportion zone-level damages to counties (data users can choose the weighting scheme that best suits their empirical analysis). *Losses from Natural Disasters* provides nominal and inflation-adjusted damages, injuries, and fatalities for each natural disaster reported by NOAA. Our county-level estimates are particularly accurate for severe disasters and can be easily aggregated to different levels, such as county-month, county-month-disaster type, state-year, and so on. Finally, we use our data to discuss three facts on the economic and human costs of natural disasters.

Losses from Natural Disasters is publicly available and regularly updated at newyorkfed.org/research/policy/natural-disaster-losses. This webpage also includes interactive maps, FAQs, data dictionaries, and other details about the dataset. Figure 1 shows a heat map of total county-level damages from floods, hurricanes/tropical storms, and coastal disasters (top panel) and wildfires (bottom panel) between 1996 and 2023 using our data.[1]

[1]Coastal disasters are astronomical low tide, coastal flooding, high surf, rip current, and storm surge/tide.

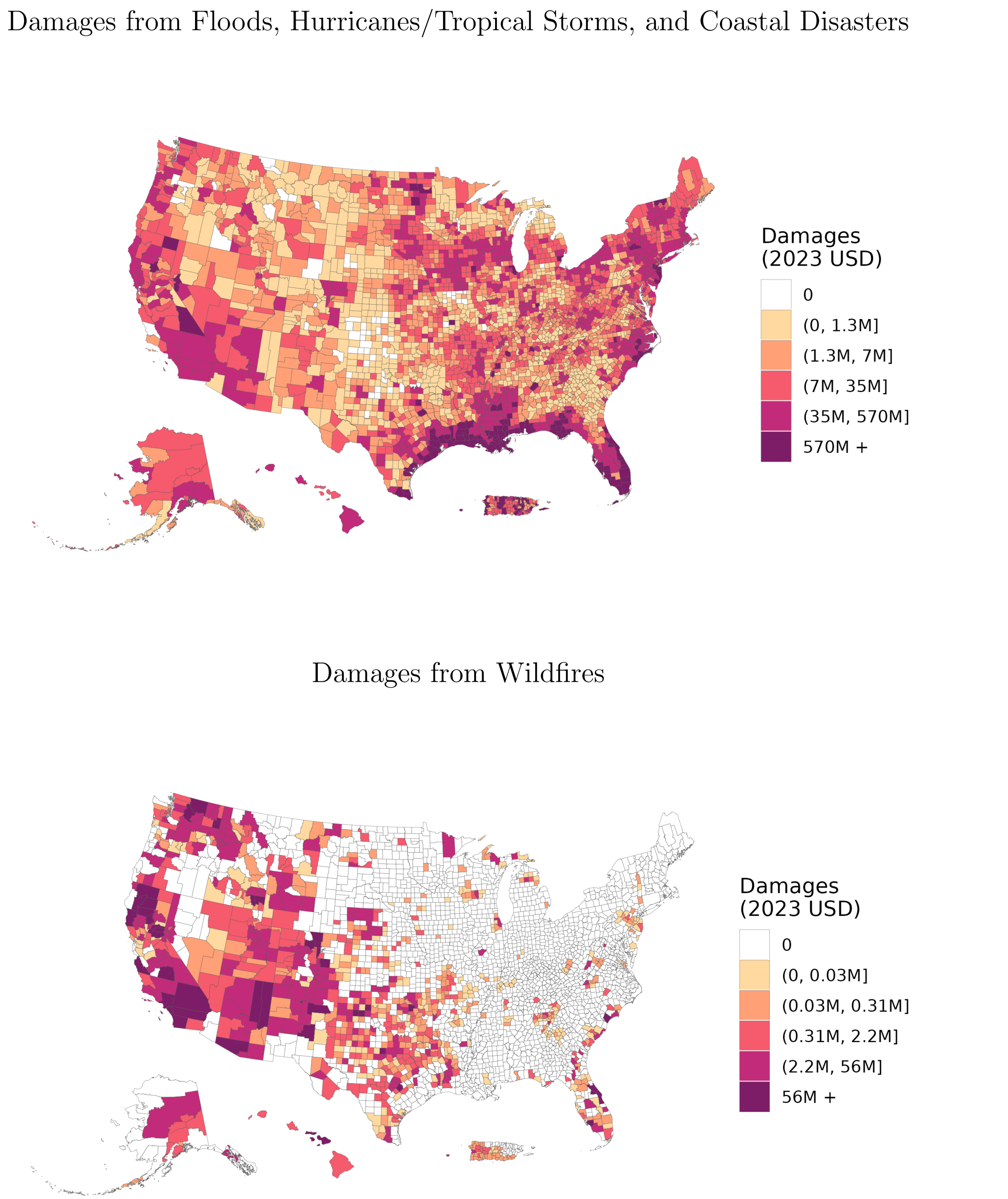

Figure 1: Total damages from flooding, hurricanes/tropical storms, coastal disasters, and wildfires from 1996 to 2023. This figure shows a heat map of total cumulative county-level damages from flooding, hurricanes/tropical storms, and coastal disasters (top panel) and wildfires (bottom panel) between 1996 and 2023. Table OA.3 provides definitions of each disaster type. Damages are inflation adjusted to December 2023 USD using the CPI. Figure OA.2 shows damages from all disaster types and droughts. Sources: NOAA, U.S. Census Bureau.

These maps, obtained using population-based weights, document that Florida, the Southeast, and parts of the East Coast have suffered the most from flooding, hurricanes, and coastal disasters, while the West has been particularly affected by wildfires.

Our main data source is the Storm Events Database (SED), an official NOAA publication. The SED records significant or unusual weather phenomena that are collected in a national database by the National Weather Service (NWS) and classified into over 55 types of weather events since 1996 (we further group disaster types into 13 broader categories). The SED reports (i) direct property damages, (ii) crop damages, and (iii) direct and indirect fatalities and injuries. As anticipated, the location of each event is either a county or a zone, where the NWS uses zones to allow for more accurate forecasts due to "such things as elevation or proximity to large bodies of water."

Our methodology to map all events to counties is based on three steps. First, we use historical maps to identify which county (or counties) each zone intersects. Second, for zones that overlap multiple counties, we use Census block group data to construct a set of weights that allocate damages to counties based on the spatial distribution of population, housing stock, and economic activity (employment and income). For example, if 75% of a zone's population lives in county A and the remainder in county B, the population weights assign 75% of the reported damages in that zone to county A and 25% to county B. The mapping from zones to counties and the set of weights lead to a crosswalk from zones to counties. We build this mapping for the current and historical vintages of NOAA's geographic units so that the crosswalk is based on boundaries that were in effect at the time of the disaster.

Our methodology leads to county-level estimates that are particularly accurate for severe disasters. We start by documenting that our weighting schemes lead to substantially different estimates compared with naïve "equal weighting" schemes (commonly used in existing work) in the context of the 2017–2023 Western Wildfires and Hurricane Katrina, two disasters largely studied in the literature (e.g., Issler et al., 2021; Deryugina et al., 2018). We then analyze the full sample of disasters from 1996 and 2023 and document that our estimates systematically deviate from a naïve equal-weighting scheme, especially for more damaging disasters. This empirical regularity is consistent with the higher likelihood of higher damages in urban areas and the observation that several of the especially costly disaster types (e.g., hurricanes and wildfires) are only reported at the zone level by NOAA.

We also document three facts about the economic and human costs of natural disasters. First, the severity of disasters is very skewed with a small share of disasters being responsible for the majority of damages, injuries, and fatalities. For example, while the median damage for a county-year hit by a disaster is $4.6 per person, the 99th percentile is a staggering $4,355.8. This skewness is particularly pronounced for hurricanes/tropical storms, coastal disasters, and droughts—and is also present when looking at injuries and fatalities. Second, the frequency and severity of damages are negatively correlated across disaster types. In other words, very damaging disasters tend to be relatively infrequent while less damaging ones tend to be particularly frequent. For example, droughts, hurricanes/tropical storms, and coastal disasters are extremely damaging and infrequent, while wind and floods are frequent and less damaging. Third, some types of disasters, such as hurricanes/tropical storms, floods, and coastal disasters, have become more severe in the last 25 years, while other disaster types, such as drought and wildfires, have become less severe.

Related literature. Our new, comprehensive, publicly available dataset on damages, injuries, and fatalities from natural disasters contributes to the large and growing literature that uses county-level data on damages from natural disasters in economics (e.g., Barrot and Sauvagnat, 2016; Fried, 2022) and finance (e.g., Bernile et al., 2017; Heimer et al., 2019; Ge, 2022; Alok et al., 2020; Li et al., 2024; Morse, 2011; Cortés and Strahan, 2017; Dessaint and Matray, 2017; Ge and Weisbach, 2021; Diamond et al., 2024; Ersahin et al., 2024; Aretz et al., 2019; Schüwer et al., 2019; Choi et al., 2023; Huynh and Xia, 2023; Dlugosz et al., 2024).

Outline. The remainder of the paper is structured as follows. Section 2 presents the SED data. Section 3 discusses our methodology to construct county-level damages, injuries, and fatalities. Section 4 shows that our weighting scheme leads to different estimates compared with naïve equal weighting, especially for severe disasters. Section 5 presents three facts about direct damages, injuries, and fatalities from natural disasters. Section 6 concludes.

2 The official data source

We now provide a brief description of our main data source. The source of our estimates is the Storm Events Database (SED), an official publication of the National Oceanic and Atmospheric Administration (NOAA). The reader is referred to NWS Directive 10-1605 for a detailed discussion of the SED data.

The unit of observation in the SED is an "event." An event must meet one of the following criteria: (i) the occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce; (ii) unusual weather phenomena that generate media attention (e.g., snow flurries in South Florida); or (iii) other significant meteorological events, such as record maximum or minimum temperatures.

The underlying data comes from a variety of sources, including, among others, National Weather Service (NWS) trained spotters, county, state, and federal emergency management officials, local law enforcement, and media reports.[2] The disparate records are collected, compared, and verified by "storm data preparers" at the 123 NWS Weather Forecast Offices (WFOs). After this verification procedure, the WFOs send the data files to the NWS headquarters, which standardizes the format and updates the national database. The SED is updated with approximately a three-month lag (e.g., the data for January is usually made available in April). From 1996 to the present, NOAA has included over 55 types of weather events in the database, ranging from hurricanes to dust storms and flash floods. Table OA.3 provides a complete list of the event types in the SED data. The table also provides a categorization of each event type into a broader "disaster type" category.

We primarily rely on two sets of variables from the SED—those that quantify losses from events and those that document their location.

[2]Table OA.1 and Table OA.2 report the share of events in the NOAA data by source. Approximately 65% of the events come from NOAA/NWS or other government-affiliated officials.

Losses from natural disasters. The SED reports estimated direct property and crop damages, along with direct and indirect fatalities and injuries.

Property damage refers to damage inflicted to private property as well as public infrastructure and facilities. Damage is reported if "a reasonably accurate estimate" is available from an insurance company or other qualified entities including "emergency managers, U.S. Geological Survey, U.S. Army Corps of Engineers, utility companies, and newspaper articles." Crop damages are obtained from the "U.S. Department of Agriculture (USDA), the county/parish agricultural extension agent, the state department of agriculture, crop insurance agencies, or any other reliable authority."

The SED only reports direct damages, i.e., monetized values of physical destruction. Indirect damages, those that happen after the event and are a consequence of direct losses, are not included in the damage estimates. For example, a ruptured power line that falls on a home during a tornado results in *direct* damages. Subsequent (indirect) losses may occur if local businesses are forced to close due to a lack of power from the downed line. NOAA refers to these indirect damages as "other related costs," and Storm Data Preparers are instructed not to include them in the SED.

The SED also records direct and indirect fatalities and injuries. Storm data preparers are responsible for determining the number of fatalities and injuries and whether they are a direct or indirect result of the event. Direct fatalities and injuries are those in which the "active" agent is the weather event itself or the debris created by the event. Indirect fatalities and injuries occur near an event, but are not "directly caused by impact or debris from the event." For example, "fatalities/injuries caused by wind-driven debris during a hurricane" are direct, and "a vehicle accident caused by a hurricane-related missing traffic signal" is considered an indirect injury or fatality.

Location of natural disasters. The SED consistently documents the location of disasters using geographic areas, a field populated for all observations in the SED. The type of geographic area in the SED depends on the event type. As shown in Table OA.3, 10 types of events are reported at the county level and 34 types of events are reported at the zone level. The remaining 11 event types are designated for marine zones and categorize events that do not occur over land. Zones were established by the NWS to allow for more accurate forecasts because of the "differences in weather within a county due to such things as elevation or proximity to large bodies of water."[3] For example, one county may be split into two zones, a coastal and inland portion, or a zone may trace the boundaries of a valley which overlaps multiple counties. Generally, zones are smaller than counties, but an individual zone can intersect with more than one county.

Importantly, events are defined to be zone-specific or county-specific. Hence, if the same natural disaster (or storm system) affects multiple zones or counties, the data features a separate event (i.e., a separate observation) for each affected zone or county.[4] To connect events that are part of the same natural disaster but occur in different areas, the SED assigns each event to a broader "episode." We preserve this event-to-episode mapping to allow researchers to track the spatial distribution of losses from a given disaster or storm system.

3 Mapping losses to counties

We now discuss how we construct our county-level estimates of losses from natural disasters. Specifically, we describe how we build crosswalks from historical maps to allocate damages in the SED to the county level using weights that reflect the spatial distribution of population, housing stock, and economic activity.

The data challenge with Public Forecast Zones. While allowing for more accurate weather forecasts, zones prevent the SED from being readily used for county-level analyses. Indeed, about 40% of all events are reported at the zone level in the SED. Although NOAA provides "zone-county correlation files" that map each zone to one or more counties, two limitations prevent these crosswalks from being sufficient to accurately calculate county-level damages. First, NOAA regularly changes the zone boundaries and identifiers (e.g., splitting

[3] See https://www.weather.gov/gis/PublicZones for more details about zones.

[4] We use the term "storm system" to refer to broader disasters/weather phenomena such as Hurricane Harvey or the 2023 Hawaii Firestorms.

one zone into two), but the correlation files only contain a mapping for the most recent vintages of the zones. Hence, merging historical events with the current crosswalk leads to unmatched events and potentially inaccurate mapping. Second, the crosswalks do not provide a rule for apportioning zone-level damages to counties when the zone spans multiple counties, which occurs for approximately 22% of zones as of 2023.

Given these issues, we construct our own crosswalks using zone and county maps. The crosswalks link each zone to all counties that the zone overlaps. For zones that overlap multiple counties, we calculate a set of weights that can be used to allocate damages to counties based on the share of a zone's population, housing stock, or economic activity located in each overlapping county. Crucially, we construct these crosswalks using current *and historical* vintages of the NOAA zones, ensuring that our allocation of damages to counties is consistent with the zone boundaries at the time the event occurred.

Constructing crosswalks. To build the crosswalks, we overlay shapefiles of NOAA zones and U.S. counties from the same year as the vintage of the NOAA zones.[5] Shapefiles are a data format that contain a collection of polygons oriented in space. The intersection of zones and counties generates a new map consisting of smaller and mutually exclusive spatial subunits. Each of these subunits is a unique zone-county pair with a non-zero geographic intersection. Using Census block group-level data, we next calculate the area, population, employed population, aggregate income, and the number of housing units in each zone-county pair. In the case of population, we then calculate the weights for each zone-county pair by dividing the population of the zone-county pair by the total population of the zone. We use the same methodology for weights based on area, employed population, aggregate income, and number of housing units.

For example, if 80% of a zone's population is located in county A and 20% in county B, our population-based weights allocate 80% of damages from weather events in the zone to county A and the remaining 20% to county B. A zone located entirely within one county

[5]We construct multiple crosswalks (one per year) for vintages that were in effect over multiple years.

has a weight of 1, so all damages are assigned to that county. We construct similar weights using different weighting variables, namely geographic area, employed population, aggregate income, and the number of housing units. We benchmark our methodology against a naïve equally-weighted weighting scheme (used, to the best of our knowledge, by commercially available datasets) that distributes damages equally among all counties that intersect the affected zone.

Example: Zone 504 in Washington state. To make this procedure more concrete, Figure 2 provides an example of the crosswalk construction using zone 504 in Washington state from the 2017 vintage of zone boundaries. Panel A shows the zone overlaid onto the Washington county map, and Panel B zooms in on the three counties the zone overlaps, namely Mason, Thurston, and Lewis counties. Panel C illustrates the first step of the procedure, i.e., the spatial intersection of the zone and county boundaries. The result is a dataset where there is only one observation for each zone-county pair. The three colored polygons in Panel C represent each observation in the spatial intersection.

Next, we construct a set of weights that apportion disaster damages from zone z to counties $c_1, \ldots, c_n$ (in this example, $n = 3$). Formally, the weight for each zone-county intersection $z \cap c_i$ is

$$w^f_{z \cap c_i} = \frac{f(z \cap c_i)}{\sum_{i=1}^{n} f(z \cap c_i)},$$

where $f(z \cap c_i)$ is the value of one of our weighting variables (area, population, employment, number of housing units, or income) for the zone-county intersection. Intuitively, the weights represent the share of the zone's total population (or any other weighting variable) that is located in a particular zone-county subunit. The naïve equally-weighted weighting scheme for each zone-county pair is simply calculated as $1/n$.

We construct the weights by calculating the value of the underlying weighting variable for each zone-county pair. For the area weighting variable, we perform this calculation using the Geographic Information System (GIS) software. Values of the economic and demographic variables cannot be directly obtained because these subunits do not conform to standard administrative boundaries. Hence, we estimate these values using American Community Survey (ACS) 5-year data at the block group level. The procedure for obtaining our estimates

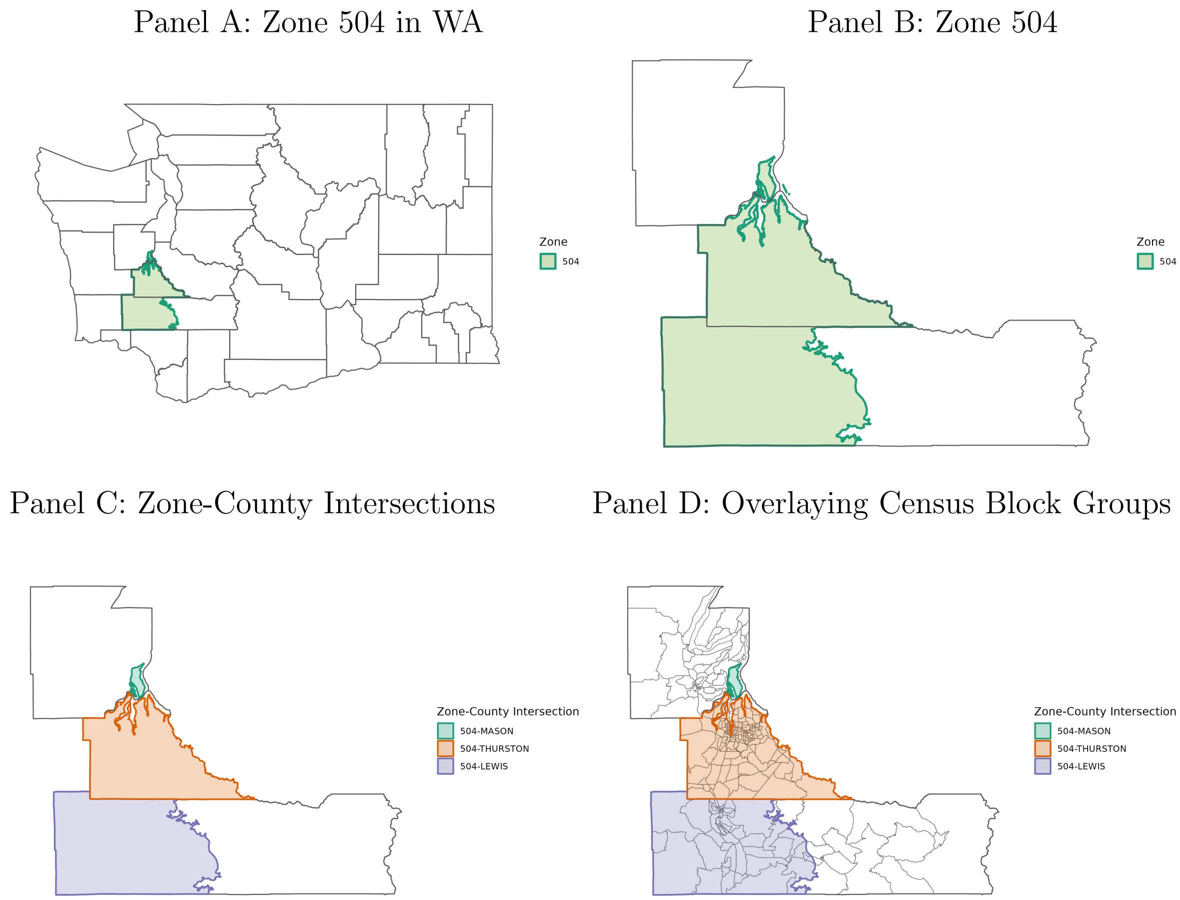

Figure 2: Example of crosswalk construction. This figure shows an example of crosswalk construction for zone 504 in Washington state. Panel A shows the zone overlaid onto the county map. Panel B zooms in on Mason, Thurston, and Lewis counties—the counties that overlap with zone 504. Panel C and Panel D illustrate the first and second step of the procedure, respectively. Sources: NOAA, U.S. Census Bureau.

is shown in Panel D of Figure 2, which overlays census block groups onto the zone-county subunits. We calculate the value of the weighting variable by summing across all block groups located in the zone-county pair. If a block group is located in multiple zone-county pairs, before adding the weighting variable to the zone county-total, we multiply it by the share of the block group's geographic area that is located in the zone-county pair.

In our example of zone 504 in Washington state, the population weight (0.799) and economic weights (0.820, 0.842, 0.793 for employment, income, and housing stock, respectively) for Thurston County are more than double than its equal weight (0.333) and area-based weight (0.404). This discrepancy is due to this portion of Thurston County containing the city of Olympia. Interestingly, the naïve equal weights are also very inaccurate for Mason county which, as shown in the figure, only shares a very tiny intersection with zone 504.

Final steps: 50 states (plus D.C. and Puerto Rico) and 46 vintages. The process used in this example is executed for each zone in all 50 states plus D.C. and Puerto Rico. The crosswalks for each state are then appended to form a single crosswalk for each NOAA map. We repeat this process for the 46 vintages of NOAA maps that were effective between 2006 and 2023. For vintages that were in effect across multiple years, we construct multiple crosswalks (one for each year) using the corresponding county boundaries and Census block group data. Hence, for this period, we are able to merge the events with the crosswalk constructed from the zone boundaries that were in effect at the time of the event. For events that occurred from 1996 to 2006, we merge events with a crosswalk created from the oldest vintage of zones for which we obtained a shapefile map, namely 2006.

As a final step, we merge all zone-level events with the crosswalk from the zone boundaries that were in effect at the time of the event. We append this data to the events in the SED that are reported at the county level. These events are assigned a weight of one for each of the six methodologies since they occur only in one county.

The final dataset. Our final dataset is an event-level dataset that can be collapsed to the county level by selecting a weight type and summing the weighted damages across all events in the county. We group events in 13 broad disaster types: coastal disaster, winter weather, wind, flood, drought, wildfire, tornado, hail, heat, hurricane/tropical storm, thunderstorm/rain, tsunami/seiche, and other. The data can be easily aggregated to different levels such as county-month, county-month-disaster type, state-year, and so on.

4 Precise damage estimates

We now show that the weighting schemes in our methodology lead to estimates that are particularly accurate for severe disasters. First, we document substantial differences in estimates compared to naïve equal weights in the context of the 2017–2023 Western Wildfires and Hurricane Katrina. We then show, more formally, that the accuracy of our data increases in disaster severity.

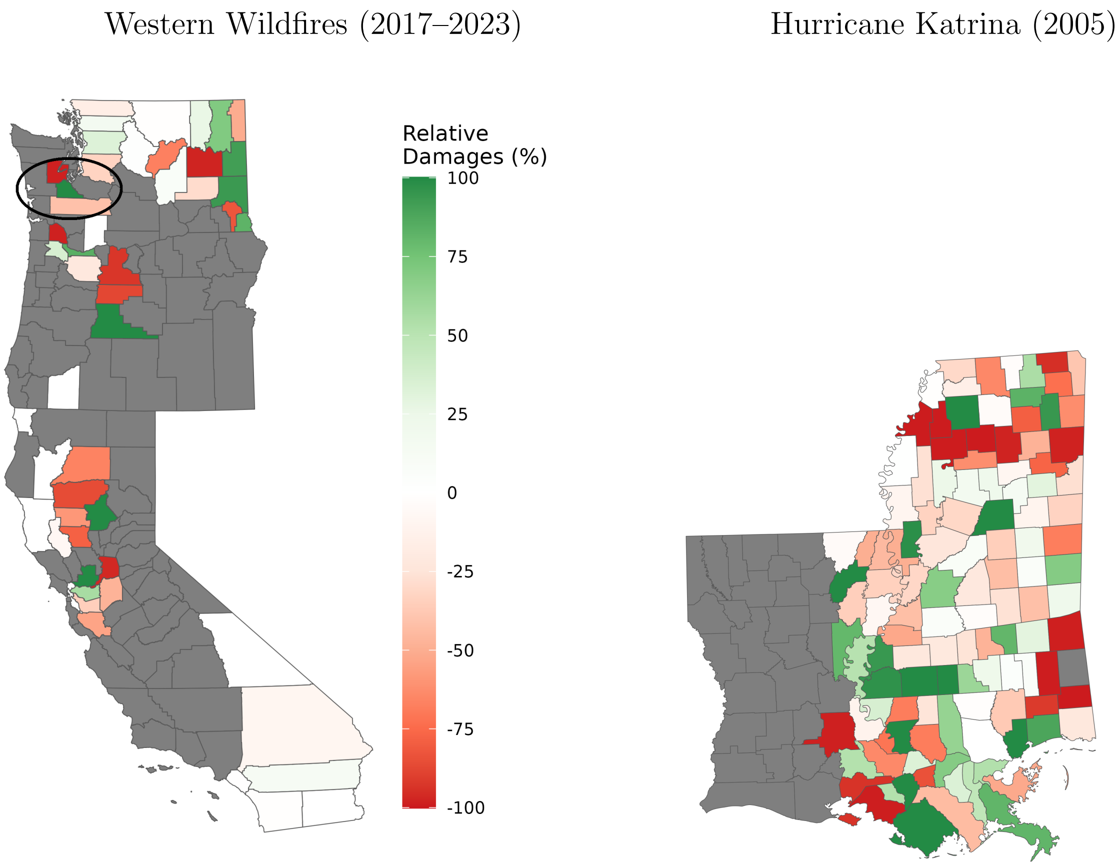

Figure 3: Population-weighted relative to equal-weighted damages: 2017–2023 Western Wildfires and Hurricane Katrina. This figure plots the relative difference between population-weighted and equal-weighted damages for the 2017–2023 Western Wildfires in Washington, Oregon, and California (left panel) and Hurricane Katrina in Mississippi and Louisiana (right panel). We define Hurricane Katrina to include all events with a disaster type of hurricane/tropical storm, coastal disaster, or flood with a start date between August 25, 2005, and August 30, 2005. See Table OA.3 for more details on which events are included in these disaster types. The relative distance metric is defined as $d_c^{Population|Equal} =$ (Population Weighted Damages$_c$ − Equal Weighted Damages$_c$)/Equal Weighted Damages$_c$. Sources: NOAA, U.S. Census Bureau.

Hurricane Katrina and the 2017–2023 Western Wildfires. We now document the importance of the weighting scheme to accurately compute damages from natural disasters. We start by focusing on the 2017–2023 Western Wildfires and Hurricane Katrina, two disaster types (wildfires and hurricanes) reported at the zone-level by NOAA. These episodes have been widely studied in the literature. For example, Issler et al. (2021), McConnell et al. (2021), and Biswas et al. (2023) investigate the impact of wildfires on migration and the housing market, and Vigdor (2008), Gallagher and Hartley (2017), Deryugina et al. (2018), and Groen et al. (2020) examine the economic and financial consequences of Hurricane Katrina.

Figure 3 shows that damages estimated using population-based weights differ substantially from damages estimated using equal weights. The left panel focuses on county-level damages from wildfires in Washington, Oregon, and California from 2017 to 2023, where the black circle highlights the counties of Lewis, Mason, and Thurston from our example in Section 3. The colors indicate the difference between population-weighted and equal-weighted damages, highlighting how equal weights often lead to an underestimation (green) or overestimation (red) of damages compared to population-based weights. Building on the example in Figure 2, note that equal weights overstate damages in Lewis and Mason counties, but understate damages in Thurston county which contains the city of Olympia. The right panel also documents substantial deviations between the two measures for Hurricane Katrina in Mississippi and Louisiana.

Figure OA.3 to Figure OA.7 in the Appendix show the county-level relative difference metric between equal-weighted damages and damages based on the other five weighting schemes for all counties during the entire sample period. Our weighting schemes lead to particularly different estimates in the Mountain and Pacific West, while differences are more limited in the Midwest and East Coast.

Accuracy of estimates increasing in disaster severity. We now show that the precision of our data increases for more damaging disasters. To this end, we compare estimates obtained using equal weights to, again, estimates obtained using weights that reflect the spatial distribution of population.

We calculate a relative distance metric for each county c and episode e using the formula:

$$d_{ec}^{Population|Equal} = \frac{\text{Population Weighted Damages}_{ec} - \text{Equal Weighted Damages}_{ec}}{\text{Equal Weighted Damages}_{ec}}. \quad (1)$$

Figure 4 shows a binscatter plot where episode-county level observations are plotted based on their relative distance metric (absolute values on the y-axis) and the severity of episode losses (log damages on the x-axis). The figure shows that the discrepancy between damages calculated using equal weights and damages calculated using population-based weights increases with the severity of natural disasters, suggesting that the accuracy of our data is

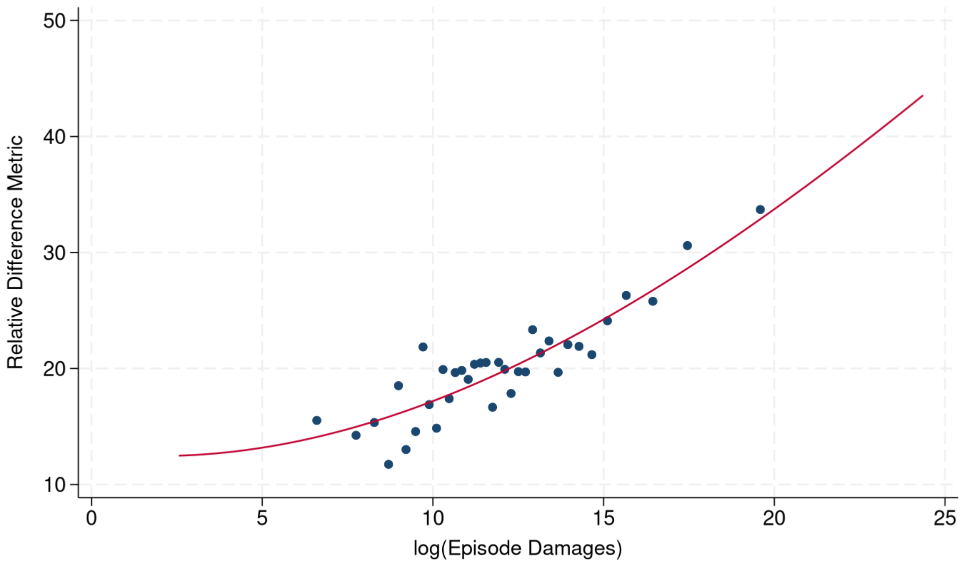

Figure 4: Absolute relative difference increasing in disaster size. This figure shows a binscatter plot using the methodology of Cattaneo et al. (2024). The y-axis shows the absolute value of the relative distance metric against episode-level population-weighted damages on the x-axis. The sample includes all episode-county observations with non-zero damages from 1996 to 2023. The absolute relative distance metric between population- and equal-weighted damages is defined in (1). Sources: NOAA, U.S. Census Bureau.

particularly pronounced for severe disasters.[6] This positive relationship between episode-level damages and the relative difference metric can be explained by (i) likely higher damages in urban areas and (ii) several costly disaster types, such as hurricanes and wildfires, being reported at the zone level by NOAA.

5 Damages, injuries, and fatalities

We now present a set of facts, based on our data, about damages, injuries, and fatalities from natural disasters between 1996 and 2023.

Table 1 presents per capita damages (inflation adjusted dollar values; Panel A), injuries (per 100,000 persons; Panel B), and fatalities (per 100,000 persons; Panel C) at the county

[6]While the distance metric discussed here compares the equal and population weighting methodologies, this metric can also be easily calculated to compare equal weighting to weights based on area, employment, income, or housing stock. The insights presented in this section (based on population) carry on to the comparison of equal weighting to area, employment, income, or housing stock weighting.

level over the period from 1996 to 2023 for all types of disasters, as well as the same statistics broken down by disaster type for the seven most damaging disaster types (hurricane/tropical storms, floods, coastal disasters, tornadoes, wildfires, hail, and drought)[7]. The first column shows the *frequency* of disasters, namely the number of county-year observations with non-zero damages (injuries, fatalities) from a given disaster type. The next four columns show the *severity* of disasters. Specifically, these four columns show the distribution of total damages (injuries, fatalities) at the county-year level, where we use population-based weights and then divide by the total population at the county-year level to obtain per capita statistics. Finally, the last three columns show the means of per capita damages (injuries, fatalities) for three subsample periods: 1996–04, 2005–13, and 2014–23.

There are three main takeaways. First, the severity of disasters is highly skewed. Specifically, the distribution of damages, injuries, and fatalities shows that a small share of disasters accounts for the majority of these outcomes. Consider, for example, the 67,096 county-year observations that have non-zero damages in our sample. The mean damage for a county hit by a disaster is \$285.9 per capita, but the median is only \$4.6, and the 99th percentile is a staggering \$4,355.8. This skewness is particularly pronounced for hurricanes/tropical storms, coastal disasters, and droughts—note that droughts can be particularly damaging. In terms of injuries, floods are extremely dangerous, followed by tornadoes, and hail. The distribution of per capita injuries is also highly skewed, with a median of 2.4, mean of 14.6, and 99th percentile of 174.5 across all disaster types. Finally, tornadoes are associated with the highest mean fatalities per 100,000 persons at 11.1, but floods and coastal disasters cause fatalities in the greatest number of county-year observations. Similar to damages and injuries, the distribution of per capita fatalities is very skewed.

Second, frequency and severity are negatively correlated across disaster types, i.e., very damaging types of disasters tend to be relatively infrequent compared to less damaging ones. One the one hand, consider droughts, hurricanes/tropical storms, and coastal disasters. These disasters can be extremely severe, with mean per capita damages of \$1,492.5, \$1,240.1,

[7] See Table OA.3 for a mapping of NOAA's event types into these broader disaster types.

Summary statistics calculated using county-year-disaster type observations with non-zero damages (Panel A), injuries (Panel B), and fatalities (Panel C) over the entire sample period (1996–2023)

Panel A — damages ($ per capita)

		Distribution of Damages				**Time Series** (means)		
	Count	Mean	p50	p90	p99	1996–04	2005–13	2014–23
All	67,096	285.9	4.6	188.3	4,355.8	235.3	378.5	237.7
Hurricane/Tropical Storm	3,473	1,240.1	5.1	766.1	21,929.2	572.8	1,399.5	1,726.9
Flood	25,389	153.1	2.2	105.6	2,471.0	123.2	119.8	225.4
Coastal	1,314	973.8	0.8	118.4	13,014.4	45.2	1,642.4	441.8
Tornado	13,163	91.2	3.4	87.5	1,474.4	81.2	135.5	52.7
Wildfire	2,100	328.6	2.0	157.4	5,187.6	729.5	178.3	418.9
Hail	12,004	92.5	1.5	109.4	2,052.4	108.3	74.3	95.7
Drought	2,795	1,492.5	66.6	2,564.0	26,786.3	1,390.7	2,289.4	285.2

Panel B — injuries (per 100,000 persons)

		Distribution of Damages				**Time Series** (means)		
	Count	Mean	p50	p90	p99	1996–04	2005–13	2014–23
All	14,950	14.6	2.4	26.1	174.5	15.4	14.3	13.7
Hurricane/Tropical Storm	242	8.1	0.5	10.5	177.8	12.7	4.8	7.3
Flood	766	37.0	2.1	24.6	884.6	60.2	14.1	6.8
Coastal	515	2.0	0.5	3.2	23.9	1.5	1.4	2.7
Tornado	2,580	30.3	7.3	66.3	347.5	26.8	33.4	31.1
Wildfire	724	9.8	1.5	20.0	118.8	6.6	11.3	9.1
Hail	225	20.9	5.0	53.8	188.2	22.2	19.5	20.5
Drought	6	513.6	2.8	2,965.3	2,965.3	.	23.3	2,965.3

Panel C — fatalities (per 100,000 persons)

		Distribution of Damages				**Time Series** (means)		
	Count	Mean	p50	p90	p99	1996–04	2005–13	2014–23
All	12,113	3.7	0.8	8.3	43.9	3.2	3.6	4.5
Hurricane/Tropical Storm	383	4.3	0.5	5.3	52.5	1.3	8.3	3.1
Flood	1,822	4.2	1.3	9.6	45.7	3.4	4.0	5.4
Coastal	1,274	1.6	0.5	3.1	17.6	1.2	1.1	2.1
Tornado	650	11.1	4.9	24.3	85.6	7.6	12.7	12.7
Wildfire	256	4.4	0.4	10.0	53.4	7.9	2.7	5.2
Hail	18	8.0	1.0	14.6	99.0	2.0	1.0	14.6
Drought	0	.	.	.	.	.	.	.

Table 1: Summary statistics: per capita damages, injuries, and fatalities. This table shows summary statistics for (i) per capita direct damages measured in dollars per person (Panel A), (ii) per capita injuries (direct and indirect) per 100,000 persons (Panel B), and (iii) per capita fatalities (direct and indirect) per 100,000 persons (Panel C) from natural disasters between 1996 and 2023. Damages are inflation-adjusted using December 2023 dollars and the CPI. We collapse damages (taking the sum) to the county-year-disaster type level using population-based weights and then divide damages by the total population at the county-year level. Column (1) displays the number of county-year observations with non-zero damages from a given disaster type. Columns (2)–(5) show mean, p50, p90, p99 of damages across county-year observations with non-zero damages from the listed disaster type. Columns (6)–(8) show mean damages during the periods 1996–04, 2005–13, and 2014–23. Table OA.3 provides more details on each disaster type.

and \$973.8, respectively. They are, however, relatively infrequent, as each of these disaster types caused damages to fewer than 3,500 county-year observations from 1996 to 2023. On the other hand, wind and floods are very frequent, affecting more than 25,000 county-year observations over our entire sample period. Fortunately, these two disaster types tend to be relatively less severe, causing mean per capita damages of \$23.3 and \$153.1, respectively. This negative correlation is robust, and survives if we measure severity using the 95th or 99th percentiles, instead of the mean of per capita damages. For a scatter plot documenting the correlation between disaster severity and frequency, see Figure OA.8.

Third, some disaster types have become more severe while others have become less severe over the last 25 years. Notably, hurricanes/tropical storms, floods, and coastal disasters have become more severe, while droughts and wildfires have become less severe. The mean per capita damages of hurricanes/tropical storms tripled from \$572.8 to \$1.726.9 from the 1996–04 period to the 2014–23 period. During the same time, mean damages increased tenfold for coastal disasters and doubled for floods. However, the comparison between these two periods shows a contraction in mean per capita damages of 79% and 43% for drought and wildfires, respectively.

6 Conclusion

We introduce *Losses from Natural Disasters*—new publicly available data on county-level damages, injuries, and fatalities from natural disasters in the U.S. The data is based on official publications of damage estimates from NOAA through the SED, which we transform to the county level using the spatial distribution of population, employment, income, and housing stock. This methodology leads to more accurate county-level estimates compared to the naïve equal-weighting schemes largely used, to the best of our knowledge, by commercially available datasets. We show that the increased accuracy is particularly pronounced for severe disasters.

We document three facts about county-level damages, injuries, and fatalities from natural disasters between 1996 and 2023. First, the severity of disasters is very skewed with a small share of disasters being responsible for the majority of damages, injuries, and fatalities.

Second, the frequency and severity of damages are negatively correlated across disaster types. Third, some types of disasters such as hurricanes/tropical storms, floods, and coastal disasters have become more severe in the last 25 years, while drought and wildfires have become less severe.

Our goal is to provide the public with comprehensive, publicly available, regularly updated data that can be easily matched with administrative datasets. We believe our data can help businesses, households, and policymakers better understand the economic and human costs of extreme weather events, thus leading to better evidence-based decision making. Our dataset also directly supports the Federal Reserve's mission by allowing timely analyses of local and regional economic activity in the aftermath of natural disasters. *Losses from Natural Disasters* is available and regularly updated at newyorkfed.org/research/policy/natural-disaster-losses.

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Supplemental Appendix

This appendix is structured as follows. Appendix A provides additional details on the SED database, on how we build the crosswalks, and how we allocate damages to counties. Appendix B presents additional figures on the distribution of damages and the relative difference between damage estimates across various weighting schemes.

A Data appendix

A.1 Background on the Storm Events Database

The Storm Events Database (SED) is an official publication of the National Oceanic and Atmospheric Administration (NOAA). The reader is referred to NWS Directive 10-1605 for additional details about this database. The unit of observation in the SED is an "event" which, according to NOAA, meets at least one of the following criteria:

1. The occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce;

2. Rare, unusual weather phenomena that generate media attention, such as snow flurries in South Florida or the San Diego coastal area; and

3. Other significant meteorological events, such as record maximum or minimum temperatures or precipitation that occur in connection with another event.

The underlying data comes from various sources, including county, state, and federal emergency management officials, local law enforcement officials, National Weather Service (NWS) trained spotters, and newspaper clipping services, among others. The disparate records are collected, compared, and verified by "data preparers" at the 123 NWS Weather Forecast Offices (WFOs). In the case an event is reported by multiple sources, Data Preparers are responsible for "using their professional judgment as to what single source is appropriate." Table OA.1 and Table OA.2 tabulate the number and percent of NOAA events between 1996 and April 2023 by reporting source and by category of reporting source, respectively. Approximately 65% of the events are reported by NOAA/NWS or other government-affiliated officials.

Source	**N Events**	**Percent of Total**
TRAINED SPOTTER	267,921	16.21
LAW ENFORCEMENT	177,724	10.75
EMERGENCY MANAGER	149,315	9.03
PUBLIC	136,747	8.27
MISSING	113,570	6.87
MESONET	69,106	4.18
NEWSPAPER	52,945	3.20
ASOS	47,450	2.87
COOP OBSERVER	46,277	2.80
GENERAL PUBLIC	40,778	2.47
BROADCAST MEDIA	40,185	2.43
DROUGHT MONITOR	38,394	2.32
AMATEUR RADIO	37,109	2.24
AWOS,ASOS,MESONET,ETC	36,447	2.20
NWS STORM SURVEY	35,590	2.15
911 CALL CENTER	34,684	2.10
DEPARTMENT OF HIGHWAYS	31,492	1.90
OFFICIAL NWS OBS.	31,121	1.88
AWOS	31,084	1.88
OFFICIAL NWS OBSERVATIONS	29,375	1.78
OTHER FEDERAL AGENCY	22,701	1.37
COCORAHS	17,931	1.08
SOCIAL MEDIA	17,723	1.07
FIRE DEPARTMENT/RESCUE	16,023	0.97
NWS EMPLOYEE	15,925	0.96
COUNTY OFFICIAL	15,566	0.94
STATE OFFICIAL	15,310	0.93
RIVER/STREAM GAGE	12,303	0.74
STORM CHASER	9,029	0.55
UTILITY COMPANY	8,136	0.49
PARK/FOREST SERVICE	7,727	0.47
SNOTEL	7,021	0.42
UNKNOWN	6,587	0.40
GOVT OFFICIAL	6,531	0.40
RAWS	5,886	0.36
NWS EMPLOYEE(OFF DUTY)	4,693	0.28
FIRE DEPT/RESCUE SQUAD	4,363	0.26
DEPT OF HIGHWAYS	3,461	0.21
POST OFFICE	2,086	0.13
C-MAN STATION	1,081	0.07
SHAVE PROJECT	893	0.05
COOP STATION	601	0.04
AIRPLANE PILOT	571	0.03
METEOROLOGIST(NON NWS)	555	0.03
LOCAL OFFICIAL	508	0.03
AWSS	437	0.03
COASTAL OBSERVING STATION	399	0.02
WLON	372	0.02
LIFEGUARD	349	0.02
INSURANCE COMPANY	316	0.02
BUOY	299	0.02
COAST GUARD	186	0.01
MARINER	111	0.01
TRIBAL OFFICIAL	100	0.01
ARPT EQUIP(AWOS,ASOS)	77	0.00
NPOP	3	0.00
WFO	3	0.00

Table OA.1: NOAA SED sources. This table shows the sources for the events as reported by NOAA in the SED from January 1996 to April 2023, together with the number of observations associated with each data source. Source: NOAA.

Source	**N events**	**Percent of total**
NOAA/NWS	727,676	44.02
Other Government Official	345,483	20.90
Public	187,014	11.31
Media Report	148,935	9.01
Other Company	8,452	0.51
Other	115,460	6.98
Unknown/Missing	120,157	7.27

Table OA.2: NOAA SED sources, aggregated by category. This table shows the sources for the events as reported by NOAA in the SED from January 1996 through April 2023, together with the number of observations associated with each data source. Source: NOAA.

After the verification procedure, the WFOs send data files to the NWS headquarters, which standardizes the format and updates the national database. The SED is updated monthly and generally lags the current month by 75 days (e.g., the data for January is usually made available on, or around, April 15th). From 1996 to present, NOAA has included over 55 types of weather events in the database, ranging from hurricanes to dust storms and flash floods.[1] Table OA.3 lists the event types in the data, and NWS Directive 10-1605 provides detailed definitions for each event type. We categorize these event types into 13 broader event groups, which include: coastal disaster, winter weather, wind, flood, drought, wildfire, tornado, hail, heat, hurricane/tropical storm, thunderstorm/rain, tsunami/seiche, and other.

The SED contains a number of variables that allow researchers to identify the geographic areas impacted by the event, the start/end time of its occurrence, along with its magnitude and resulting damages. The remainder of this section provides more details on the variables included in the SED.

Location. Generally, the location of the event is documented in two ways: (i) as occurring within a particular geographic area, and (ii) as occurring around a specific point.

(i) The geographic area for which events are reported depends on the event type, which is included as a variable in the data. 10 of the event types are reported at the county level, while 34 are designated for NWS Public Forecast Zones (zones). The remaining

[1] The database dates back as far as 1950, but with limited coverage. Specifically, from 1950 through 1954, only tornado events were recorded. From 1955 to 1995, more event types were reported, but only tornado, thunderstorm wind, and hail events were standardized to a CSV format. Information on other event types from this period is collected on PDFs of scanned paper documents or in unformatted text files. From 1996 to 2006 NOAA collected the data in Paradox format which they then converted to CSV format. From October 2006 to present, all event types have been recorded in CSV files.

Event Type	Event Group	Designator	Event Type	Event Group	Designator
Astronomical Low Tide	Coastal	Zone	Lakeshore Flood	Flood	Zone
Avalanche	Other	Zone	Lightning	Thunderstorm/Rain	County
Blizzard	Winter Weather	Zone	Marine Dense Fog	N/A	Marine
Coastal Flood	Coastal	Zone	Marine Hail	N/A	Marine
Cold/Wind Chill	Winter Weather	Zone	Marine Heavy Freezing Spray	N/A	Marine
Debris Flow	Other	County	Marine High Wind	N/A	Marine
Dense Fog	Other	Zone	Marine Hurricane/Typhoon	N/A	Marine
Dense Smoke	Wildfire	Zone	Marine Lightning	N/A	Marine
Drought	Drought	Zone	Marine Strong Wind	N/A	Marine
Dust Devil	Other	County	Marine Thunderstorm Wind	N/A	Marine
Dust Storm	Other	Zone	Marine Trop. Depression	N/A	Marine
Excessive Heat	Heat	Zone	Marine Trop. Storm	N/A	Marine
Extreme Cold/Wind Chill	Winter Weather	Zone	Rip Current	Coastal	Zone
Flash Flood	Flood	County	Seiche	Tsunami/Seiche	Zone
Flood	Flood	County	Sleet	Winter Weather	Zone
Frost/Freeze	Winter Weather	Zone	Sneaker Wave	Tsunami/Seiche	Zone
Funnel Cloud	Tornado	County	Storm Surge/Tide	Coastal	Zone
Freezing Fog	Other	Zone	Strong Wind	Wind	Zone
Hail	Hail	County	Thunderstorm Wind	Wind	County
Heat	Heat	Zone	Tornado	Tornado	County
Heavy Rain	Thunderstorm/Rain	County	Trop. Depression	Hurricane/Trop. Storm	Zone
Heavy Snow	Winter Weather	Zone	Trop. Storm	Hurricane/Trop. Storm	Zone
High Surf	Coastal	Zone	Tsunami	Tsunami/Seiche	Zone
High Wind	Wind	Zone	Volcanic Ash	Other	Zone
Hurricane (Typhoon)	Hurricane/Trop. Storm	Zone	Waterspout	N/A	Marine
Ice Storm	Winter Weather	Zone	Wildfire	Wildfire	Zone
Lake-Effect Snow	Winter Weather	Zone	Winter Storm	Winter Weather	Zone
			Winter Weather	Winter Weather	Zone

Table OA.3: Event types and geographic designators. This table shows the geographic unit used for each event type in the SED database. Our analysis disregards events reported at the marine zone geographic unit. We classify each event type into one of 13 broader event groups: coastal disaster, heat, flood, wildfire, wind, drought, winter weather, hurricane/tropical storm, wind chill, tsunami/seiche, thunderstorm/rain, tornado, and other. Source: NOAA.

event types are designated for marine zones, which do not occur over land and are not included in *Losses from Natural Disasters*. The geographic designator for each event type is reported in Table OA.3.

Zones were established by the NWS to allow for more accurate forecasts because of the "differences in weather within a county due to such things as elevation or proximity to large bodies of water" (see https://www.weather.gov/gis/PublicZones for more details). For example, one county may be split into two zones, a coastal and inland portion, or a zone may trace the boundaries of a valley that overlaps multiple counties. Generally, zones are smaller than counties, but an individual zone can intersect with more than one county.

The SED indicates whether an event is reported at the county or zone level. We also observe the state name, state FIPS code, county or zone name, and county FIPS code or zone code (depending on whether the event is designated at the county or zone level). For each observation, the data indicate the County Warning Area (CWA) in which the event occurred. CWAs are groups of counties that fall under the purview of a single WFO. WFO and CWA refer to the same geographic area.

(ii) The SED also reports the beginning and ending latitude/longitude. While more granular than a geographic area, the use of these variables is limited as they are missing for 42% of the observations. Moreover, the SED does not specify the areas surrounding the starting and ending points impacted by the event. Given these limitations, we do not use the latitude and longitude data.

Losses. The SED also includes a set of variables that quantify the losses associated with each event, including estimated property damages, estimated crop damages, direct and indirect fatalities, and direct and indirect injuries.

Property damage is reported if "a reasonably accurate estimate" is available from an insurance company or other qualified entities including "emergency managers, U.S. Geological Survey, U.S. Army Corps of Engineers, utility companies, and newspaper articles."[2] Property damage refers to damage inflicted to private property as well as public infrastructure and facilities. Estimates are reported in nominal U.S. Dollars, and are rounded to three significant digits followed by the magnitude of the value (i.e., 1.55 Billion $USD for $1,550,000,000).

Crop damages are obtained from the "U.S. Department of Agriculture (USDA), the county/parish agricultural extension agent, the state department of agriculture, crop insurance agencies, or any other reliable authority." When an event damages vegetation, if the purpose of the damaged vegetation was for harvest, the losses are recorded as crop damage, regardless of whether the intended use was commercial or personal. On the other hand, if the damaged vegetation was intended to enhance a property's appearance (e.g., lawn grass), the estimated losses are counted towards property damage.

The damages recorded in the database include only direct damages (monetized losses of physical destruction), but do not account for other indirect losses that happen after the event and are not realized as physical destruction. For example, a ruptured power line that falls on a home due to a tornado is easily observed and represents a direct physical loss to property. However, this event may have indirect costs, such as business closures due to a lack of power supply. NOAA refers to these indirect damages as "other related costs," which include items such as "snow removal, debris clearing/moving, firefighting, personnel overtime charges, public housing assistance, etc." Data prepares are instructed to not include these indirect costs into the reported property and crop damages.

Beyond damages, the SED also records direct and indirect fatalities and injuries. Data

[2] See, again, NWS Directive 10-1605 for additional details.

Preparers from the NWS Forecast Offices are responsible for determining the number of fatalities and injuries and whether they are a direct or indirect result of the event. Direct fatalities and injuries are those in which the “active” agent is the weather event itself or the debris created by the event. Indirect fatalities and injuries, on the other hand, are those that occur in the vicinity of an event, but are not “directly caused by impact or debris from the event.” For example, “fatalities/injuries caused by wind-driven debris during a hurricane” are direct and “a vehicle accident caused by a hurricane-related missing traffic signal” is considered an indirect injury or fatality.

Episodes. Each event is associated with an episode identification code, and each episode typically includes multiple events. Episodes are broader classifications of whether phenomena, which help link together the more granular events. Each observation includes an episode narrative and an event narrative that describe the general nature of the episode, the specific details of the event, and how the specific event is connected to the broader episode.

More precisely, events are defined for a single county (or zone) and are assigned a single event type from Table OA.3. NOAA uses the episode identifier to account for disasters that cover a large geographic area and cause events of different types and link the individual events. The occurrence of multiple events under a single episode arises when a storm system[3] (episode) impacts multiple counties (or zones), resulting in event-level observations for each county. Multiple events under one episode can also occur when (i) a storm system causes multiple events that occur at disjoint times or places (within county/zone), resulting in event-level observations for each time or place, or (ii) a storm system causes multiple event types such as hail and thunderstorm winds which result in event-level observations for each event type. Episodes are defined to be state and WFO specific, so that the same weather phenomenon, such as Hurricane Katrina, is reported under separate episode identification codes for the New Orleans, Louisiana WFO, and the Peachtree City, Georgia WFO (among others). Within the New Orleans episode for Hurricane Katrina, there are 27 individual events, one for each zone that was impacted.

[3] We use the term “storm system” to refer to broader disasters/weather phenomena such as Hurricane Harvey or the 2023 Hawaii Firestorms. These storm systems result in multiple event-level observations in the SED based on NOAA’s definition of events.

A.2 Data inputs

Storm Event Database. The SED is available for bulk download from NOAA's website in comma-separated values (CSV) format compressed via the *gzip* algorithm to reduce their size. There are separate files for each year, and for each year there are three files—event details, event locations, and event fatalities—which can be linked by the event identifier.

Shapefiles. We also download shapefiles for two sets of geographies: the NWS Public Forecast Zones (zones) and U.S. Census administrative geographies (counties and block groups). Shapefiles are a special data format for maps, representing a collection of polygons oriented in space. Geographic Information Softwares (GIS) can open shapefiles and display the polygons. To work with shapefiles, we use the R package sf, which is a GIS interface that allows shapefiles to be stored and manipulated in the format of a data frame, where each row is a geographic entity (e.g., a zone or a county) that points to one or more polygons that encompass the entity's area.

The first set of shapefiles we use are maps of the NOAA zones. The NOAA zone shapefiles are frequently updated (usually multiple times a year) to correct for errors in previous versions or to make substantive changes to the geographies (e.g., a single zone splitting into multiple zones). Section A.3 provides further details on updates to the zone maps. Current shapefiles can be downloaded from NOAA's website. NOAA also provided us with 46 historical zone shapefiles, dating back to June 2006.

The second set of shapefiles we use are maps of U.S. counties and block groups from the U.S. Census Bureau. For counties and block groups, we use the following vintages: 1990, 2000, and every year from 2010 to 2023. For these years, we also obtain county and block group-level information on population, employed population, aggregate income, and number of housing units from the U.S. Census Bureau.

NOAA crosswalks. The NWS also provides zone-county correlation files (henceforth "crosswalks") where each observation is a unique overlap of a zone and a county. For example, if one zone overlaps three counties, that zone will be observed three times in the dataset, one for each county intersection. The most recent versions of the crosswalks can be downloaded from the website of the NWS. As discussed in more detail in Section A.3, the availability and usefulness of these crosswalks is limited for the purpose of allocating zone-level damages to the county level. Hence, we construct our own crosswalks and use the crosswalks provided by NOAA to verify our crosswalks.

A.3 Allocating NOAA damages to counties

The problem. In the SED, approximately 40% of events are recorded at the zone level, including all hurricanes and wildfires. The innovation of *Losses from Natural Disasters* is mapping these zone-level events to the county level. Doing so consists of, broadly, the following two steps:

(i) For each event reported at the zone level, identify which counties the zone intersects.

(ii) If a single zone intersects multiple counties, apportion the zone-level damages to counties.

Given that NOAA provides a zone-county crosswalk, step (i) should, in theory, be relatively simple. In practice, this task is more complex because NOAA regularly updates its shapefiles (often multiple times each year), and the SED reports the zone identifier that was valid *at the time of the event.* However, the zone-county crosswalks that are available for download from NOAA only refer to the most recent vintages of zones. Hence, there is not a 1:1 correspondence between the zone identifiers in the SED and the zone identifiers in the zone-county crosswalk.

Figure OA.1 illustrates one example of the issue created by changes in NOAA maps. Prior to 2023, there were a number of storm events reported in zone 520 of Washington state. However, there is no zone 520 in Washington state in the current zone-county crosswalk as, on 03/08/2023, what was formerly zone 520 was split into a western and an eastern portion—which became zones 522 and 523, respectively, and zone 520 ceased to exist. The current version of the zone-county crosswalk reflects this change, but the event data are not retroactively updated, so events that occurred before 03/08/2023 in this area are reported in zone 520. Hence, these events will not merge with the current crosswalk.

To overcome this challenge, rather than merging the SED to the current crosswalk, one should use the crosswalk that was valid at the time of the event. Unfortunately, the entire history of zone-county crosswalks is not available on NOAA's website. After contacting NOAA, their staff provided us with 18 zone-county crosswalks that cover the period from November 2015 to present, which leaves missing crosswalks for the period from 1995 to October 2015.

Not only do the crosswalks not cover the entire history of the SED, they are also limited in their usefulness to address the second step of mapping the damages to the county level—apportioning zone-level damages to counties when a zone spans multiple counties. For example, if a disaster occurs in zone X, the NOAA crosswalk may tell us that zone X overlaps with counties A and B, but it does not provide any guidance as to the share of damages that should be allocated to both counties.

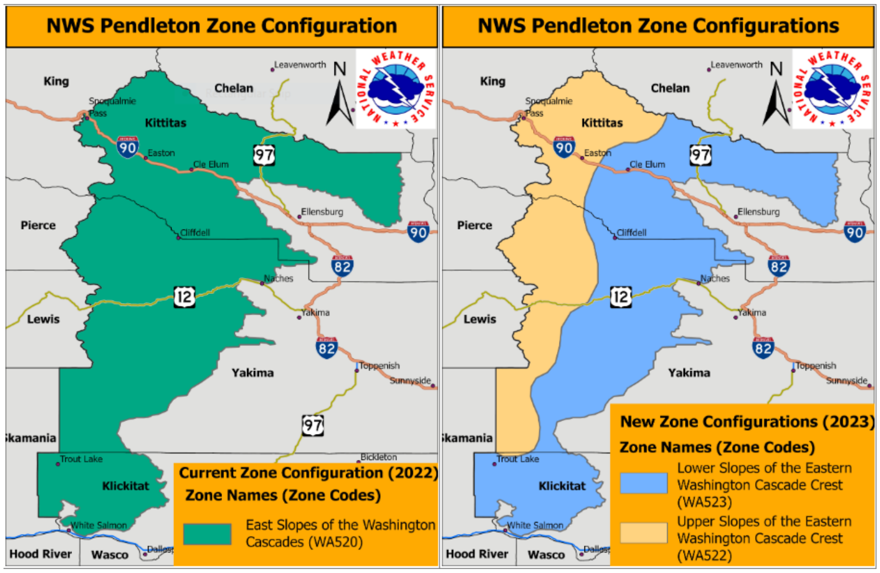


Figure OA.1: Public Forecast Zone change in Washington state.

Given the limited availability and lack of usefulness of NOAA's zone-county correlation files, we decide to construct our own crosswalks using zone and county maps. The crosswalks link each zone to all counties the zone overlaps, thus accomplishing the first step of the process. Next, we compute the share of a zone's population, economic activity, housing stock, and area that is located in each overlapping county. We use these shares as weights to allocate damages for disasters in multi-county zones, thus accomplishing the second step.

We construct these crosswalks for the current and historical vintages of zones (if the map is available), so that events can be merged with crosswalks that were valid at the time of the disaster. After constructing the crosswalks and merging with the SED, the shares can be used to allocate damages from the zone level to the county level. We now describe the process of constructing the crosswalks and the process of linking the crosswalks with the SED to allocate damages.

Constructing zone-county crosswalks. In this section, we describe the methodology for aggregating natural disaster damages from the zone level to the county level. When a zone is contained entirely within the boundaries of a single county, this process is trivial as all of the zone's damages can be allocated to that single county. However, when a zone overlaps with multiple counties, we need to choose a set of weights that distribute the damages from the zone to the multiple counties the zone intersects.

Our methodology is flexible and allows us to construct weights that distribute damages proportional to a number of relevant economic and geographic variables including population, employed population, aggregate income, number of housing units, and geographic area. To benchmark our methodology, we also distribute damages in multi-county zones via a naïve technique: equally to all counties that intersect the zone.

To build the crosswalks, our method overlays the maps of zones and counties using Geographical Information Software (GIS) through the R package sf. The two maps cover the same territory, but contain different partitions of it. The intersection of the two maps generates a new map consisting of smaller and mutually exclusive spatial subunits. From these subunits, we build a dataset where each observation is a unique zone-county pair with a non-zero geographic intersection. Using Census block group-level data, we calculate the population (aggregate income, employed population, or number of housing units) in each zone-county pair. The weights for each zone-county pair are then constructed by dividing the population of the zone-county pair by the total population of the zone. For example, if 80% of the population of a zone is located in county A and 20% in county B, then 80% of damages from weather events in the zone are allocated to county A and the remaining 20% to county B.

To make this procedure more concrete, consider the example from Washington State in Figure 2, which plots the boundaries of NOAA zone 504 from 2017 overlaid on the 2017 county map. Panel A shows the entire state, and Panel B zooms in on the three counties that the zone overlaps (Lewis, Mason, and Thurston).

The first step is to preform a spatial intersection of the zone and county boundaries. This process generates a dataset where there is one and only one observation for each zone-county pair, and each observation points to the spatial features of the geographic area. The three colored polygons in Panel C of Figure 2 make up the spatial intersection. After performing the intersection, we drop all observations for which the area of zone-county pair is less than 0.5% of the area of the entire zone. We do so to avoid treating zone-county "slivers" as meaningful units, when they are actually the result inconsistencies in the zone and county shapefiles.

Next, we apportion disaster damages from zone z to counties $c_1, \ldots, c_n$ (in the example above $n = 3$). To do so, we construct a set of weights—one for each zone-county intersection $z \cap c_i$— that can be multiplied by the damages in zone z to give the amount apportioned to county c_i. We use various sets of weights based on the distribution of population, employment, income, and housing within a given zone. More formally, the weight for each zone-county intersection $z \cap c_i$ is

$$w^f_{z \cap c_i} = \frac{f(z \cap c_i)}{\sum_{i=1}^{n} f(z \cap c_i)}. \tag{OA.1}$$

where $f(z \cap c_i)$ is the value of one of our weighting variables (area, population, employment, number of housing units, or income) for the zone-county intersection. Each weighting scheme assumes that disaster damages within a zone are distributed proportional to the weighting variable.

We also use a naïve equally-weighted scheme that distributes damages equally among all counties that intersect the effected zone (i.e., setting the weight equal to $1/n$ for each zone-county pair) to provide a comparison with our other measures.

To construct the area-based weights, we only need the area of each zone-county pair, which can be calculated from the shapefile of the intersection using the GIS software. Values of the economic and demographic variables cannot be directly obtained because these subunits do not conform to standard administrative boundaries. Hence, we estimate these values using American Community Survey (ACS) 5-year data at the block group level.

The procedure for obtaining these estimates is shown in Panel D of Figure 2, which overlays census block groups onto the zone-county subunits. To calculate the population of each zone-county pair, we proceed as follows: (i) for block groups that are entirely contained within the boundaries of a zone-county pair, we simply sum the population to the zone-county level, and (ii) when only a portion of the block group is located within a zone-county pair, we multiply the population of the block group by the area of the zone-county-block group intersection as a fraction of the area of the entire block group before summing to the zone-county-level.[4] We use the same procedure for the other economic and demographic weighting variables (employment, aggregate income, and housing stock).

Table OA.4 reports the resulting weights from our six methodologies. The demographic and economic weights for Thurston County are larger than its equal weight and area-based weight, reflecting the fact that this portion of Thurston County is more densely populated than the other two zone-county pairs (the city of Olympia is located in Thurston). The naïve equal weights are also very inaccurate for Mason county, which, as shown in Figure 2, only shares a very small intersection with zone 504.

We complete the process in the example above for all 50 states plus DC and Puerto Rico, and append the files to form a single crosswalk for each NOAA map. We construct a

[4] The share of a block group g's population that is located in zone-county subunit $z \cap c$ is calculated as

$$\frac{\sum_{b \in z \cap c \cap g} \lambda_{b,g,z,c} \text{population}_b}{\sum_{b \in g} \text{population}_b}$$

where $b \in z \cap c \cap g$ are all of the blocks that overlap with the zone-county-block group intersection, and $\lambda_{b,g,z,c}$ is the area of block b that is in the zone-county-block group intersection as a share of the total area of block b. The block-level data comes from the Decennial Census.

Zone	County	Weighting Method					
		Equal	Area	Population	Employment	Income	Housing
504	LEWIS	0.333	0.584	0.196	0.177	0.153	0.196
504	MASON	0.333	0.012	0.005	0.003	0.005	0.010
504	THURSTON	0.333	0.404	0.799	0.820	0.842	0.793

Table OA.4: Weights from counties in zone 504 in Washington state. This table shows the three observations from the crosswalk of zone 504 in Washington state that maps April 2017 zones to 2017 counties using different weighting schemes.

crosswalk for each of the 46 vintages of zones for which we were able to obtain shapefile maps. Given that maps prior to June 2006 are not available, we use the zone map from June 2006 to cover all previous events. For vintages that were in effect across multiple years, we construct multiple crosswalks for each year using the corresponding county boundaries and Census block group data. As an example, consider the vintage that was effective from November 2020 through March 2021. We construct one crosswalk to cover November 2020–December 2020 and a separate crosswalk for January 2021–March 2021 using block group data from each year.[5]

Merging the SED crosswalks. The next step in the construction of our dataset is to merge the set of all events in the SED that are reported at the zone level with the crosswalks constructed in the previous section. To do so, we use the following procedure:

(i) Left join all events with the crosswalk that was valid at the end date of the event by state and zone id.

(ii) For the set of events not merged in (i), left join all events with the crosswalk that was valid at the end date of the event by state and zone *name*. Using zone name, instead of zone id, helps us account for some data entry issues in zone id field in the SED.

(iii) For the set of events not merged in the previous steps, left join all events with the previously valid crosswalk by state and zone id. Using the previously valid crosswalk accounts for cases when the data preparers report the event in a zone that is no longer

[5]We are able to obtain ACS 5-year data at the block group-level for each year between 2010 and 2023. For the June 2006 zone shapefile, we construct two crosswalks: one for the period 1996–2004 using the 2000 block group data from the 2000 decenial census, one from 2005 to May 30, 2007 (when the next vintage became active) using 2010 block group data from the ACS 5-year estimates.

in the effective map. This may be particularly important for events that occur just after the zone map is updated by NOAA.

(iv) For the set of events not merged in the previous steps, left join all events with the previously valid crosswalk by state and zone name.

(v) Repeat steps (iii) and (iv) using the second previous crosswalks.

(vi) For the set of events not merged in the previous step, left join all events with the next crosswalk that would become valid by state and zone id. We implement this step because some entries in the data are reported to occur in zones that do not exist at the time the event occurred. This is possible because NOAA releases versions/drafts of the maps before they actually become effective, and some data preparers use these when recording events.

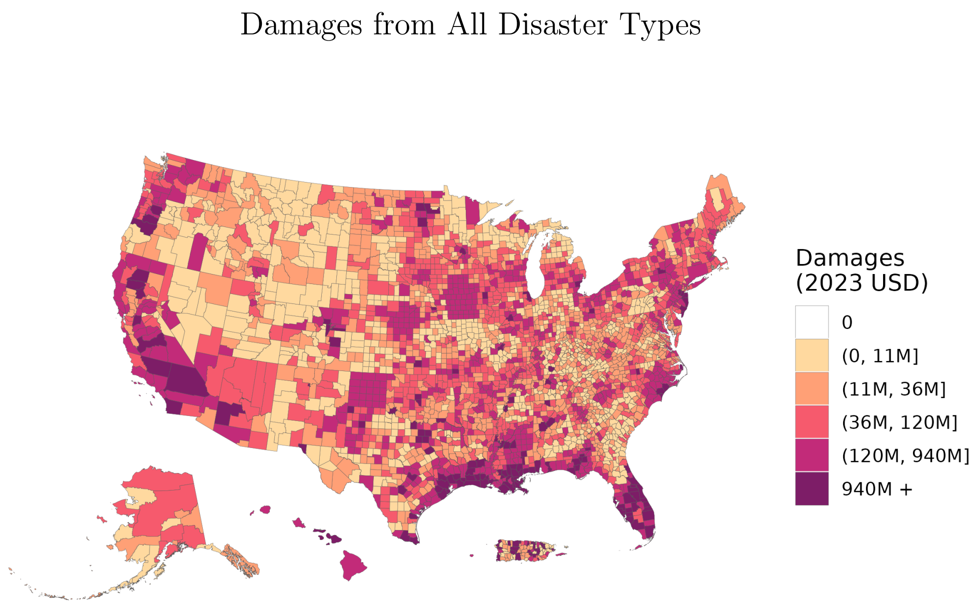
(vii) For the set of events not merged in the previous steps, left join all events with the next crosswalk by state and zone name.

(viii) Repeat steps (vi) and (vii) for the second next crosswalk.

Using this procedure, 99.7% of the total zone-level events are matched. The vast majority of the 2,026 unmatched events occur in the period between January 1996 and June 29, 2006, which can be explained by the fact that during this period we do not have the NOAA map that was valid at the time, and are thus forced to use the crosswalk constructed from the zones as of June 2006. We attempt to manually match the 2,062 events that are not matched with this algorithm to NOAA zones. We successfully manually match 1,641 of these events, leaving only 421 events which we are not able to map to the county level.

After merging the crosswalks with the zone-level events, we append this data to the events in NOAA that are reported at the county level. These events are assigned a weight of one for each of the six methodologies. Hence, we are left with an event-level dataset that can be collapsed to the county level by selecting a weight and summing the weighted damages across all events in the county.

B Additional figures



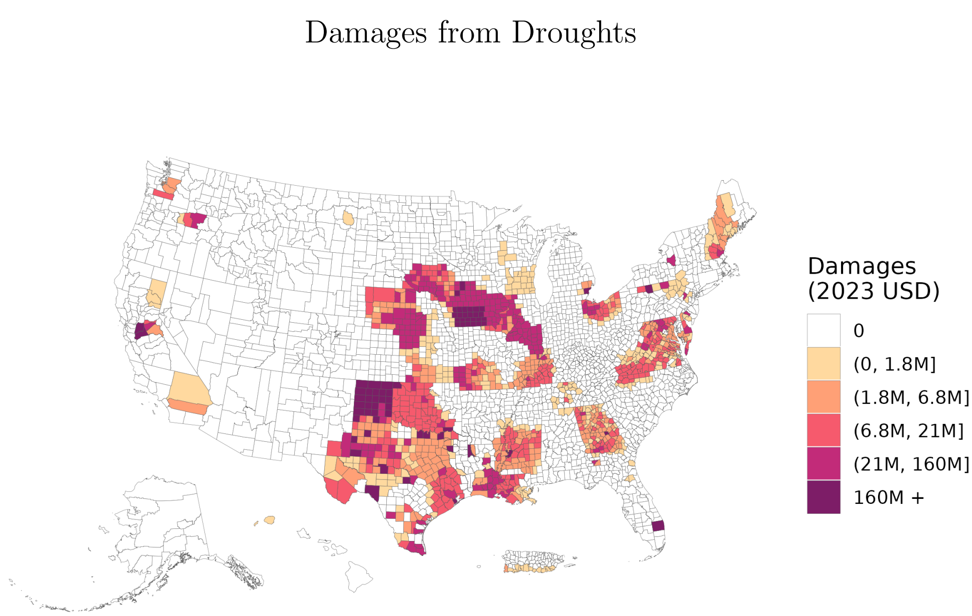


Figure OA.2: Total damages from all disasters and droughts from 1996 to 2023. This figure shows a heat map of total cumulative county-level damages from all disaster types (top panel) and droughts (bottom panel) between 1996 and 2023. Damages are inflation adjusted to December 2023 USD using the CPI. Sources: NOAA, U.S. Census Bureau.

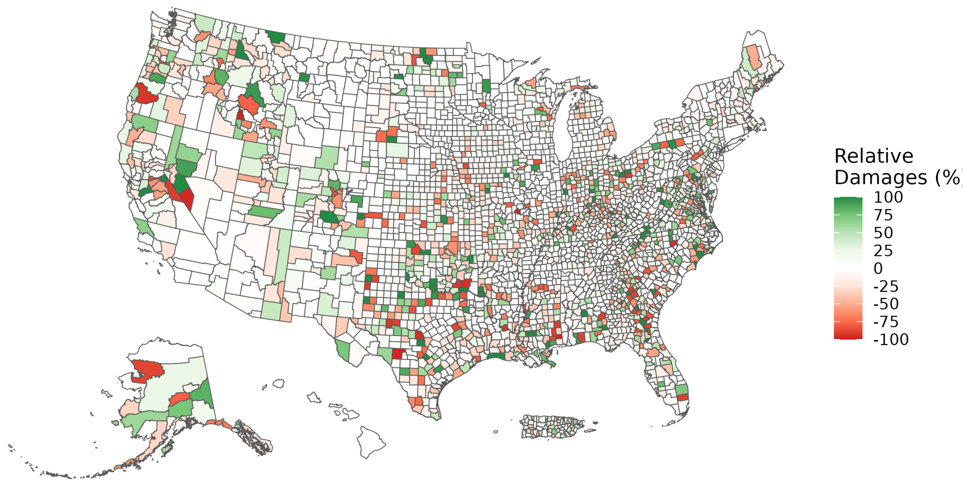


Figure OA.3: Area-weighted damages relative to equal: 1996–2023. This figure plots the relative difference between area-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2023. The relative distance metric is defined in equation (1). Sources: NOAA, U.S. Census Bureau.

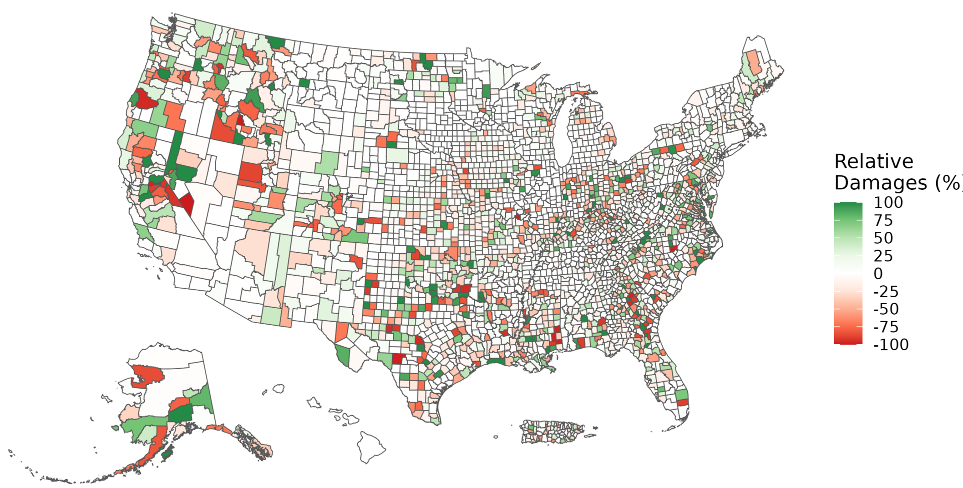


Figure OA.4: Population-weighted damages relative to equal: 1996–2023. This figure plots the relative difference between population-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2023. The relative distance metric is defined in equation (1). Sources: NOAA, U.S. Census Bureau.

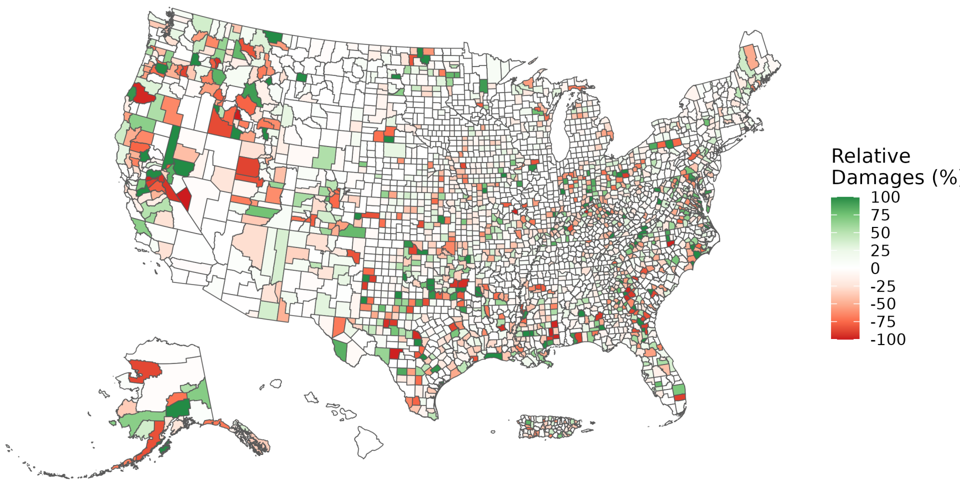


Figure OA.5: Employment-weighted damages relative to equal: 1996–2023. This figure plots the relative difference between employment-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2023. The relative distance metric is defined in equation (1). Sources: NOAA, U.S. Census Bureau.

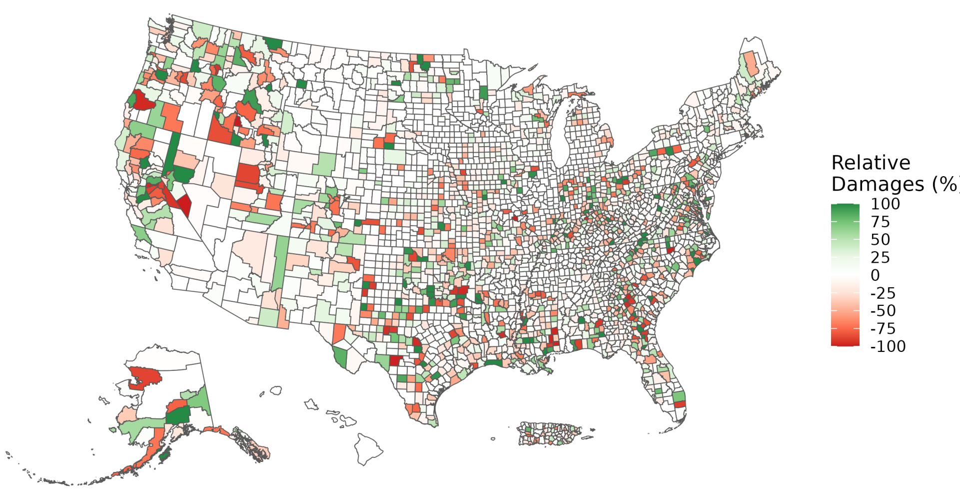


Figure OA.6: Housing stock-weighted damages relative to equal: 1996–2023. This figure plots the relative difference between housing stock-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2023. The relative distance metric is defined in equation (1). Sources: NOAA, U.S. Census Bureau.

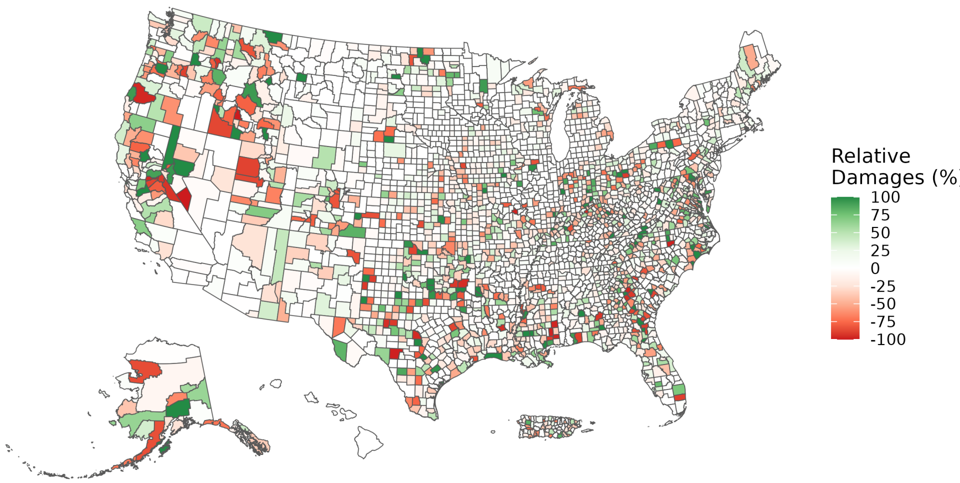


Figure OA.7: Income-weighted damages relative to equal: 1996–2023. This figure plots the relative difference between income-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2023. The relative distance metric is defined in equation (1). Sources: NOAA, U.S. Census Bureau.

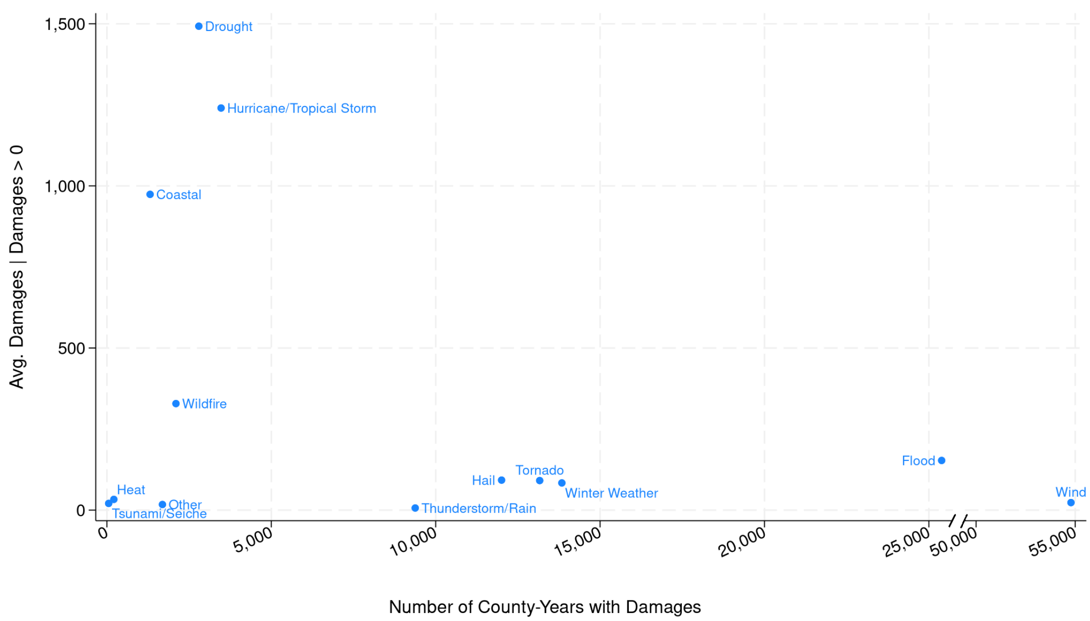


Figure OA.8: Negative correlation between disaster severity and frequency. This figure shows a scatter plot with the frequency of disasters (number of county-years with non-zero damages) on the x-axis and the severity of disasters (average damages conditional on non-zero damages) on the y-axis from 1996 to 2023. Note that we break the x-axis from 25,000 to 50,000. Sources: NOAA, U.S. Census Bureau.