Losses from Natural Disasters: New County-Level Data and Resilient Consumer Spending*

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Abstract

We introduce *Losses from Natural Disasters*, the first comprehensive public dataset on county-level damages, injuries, and fatalities from U.S. natural disasters, and document new facts about consumer spending and household financial strain around extreme weather. We map NOAA meteorological zones to counties using geographic tools and data on population, housing, and economic activity. Using transaction and consumer credit data, we find that spending falls sharply when hurricanes and coastal disasters begin but recovers within a week, while the share of borrowers with high credit card utilization remains elevated for several quarters. Despite large damages, wildfires show no comparable spending response.

JEL Codes: D12, G51, Q54.
Keywords: Natural disasters, consumer spending, credit card debt.
Link to data: **newyorkfed.org/research/policy/natural-disaster-losses**

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1 Introduction

Natural disasters can disrupt local economies and strain household finances. Consumers may cut spending and rely on credit, businesses may face operational disruptions, and governments may incur emergency response and recovery costs. Assessing these consequences requires granular information on where disasters occur and the losses they cause. Yet, limitations in official data hinder analyses of the economic and human costs of natural disasters. The National Oceanic and Atmospheric Administration (NOAA) collects nationwide estimates of damages, injuries, and fatalities, but nearly 40% are reported for meteorological "zones"—geographic units that may span several counties or cover only part of one (e.g., a valley spanning multiple counties or the coastal portion of a single county). Because these zones do not align with administrative boundaries, NOAA losses cannot be readily linked to the economic data needed to study how local economies and households respond to disasters.

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.[1] 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. Figure 1 shows damages from floods, hurricanes, and coastal disasters (top panel) and wildfires (bottom panel) from 1996 to 2025: 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.[2] To illustrate one application of our data, we then leverage transaction-level data on consumer spending and consumer-level credit card use and find that (i) consumer spending falls sharply with hurricanes and coastal disasters but returns to its pre-disaster level within a week, (ii) wildfires, while very damaging, show no detectable spending contraction, and (iii) the share of borrowers with high credit card use remains elevated for several quarters after hurricanes and coastal disasters.

[1] *Losses from Natural Disasters* is regularly updated at newyorkfed.org/research/policy/natural-disaster-losses. This webpage also includes interactive maps, FAQs, data dictionaries, and other details.

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

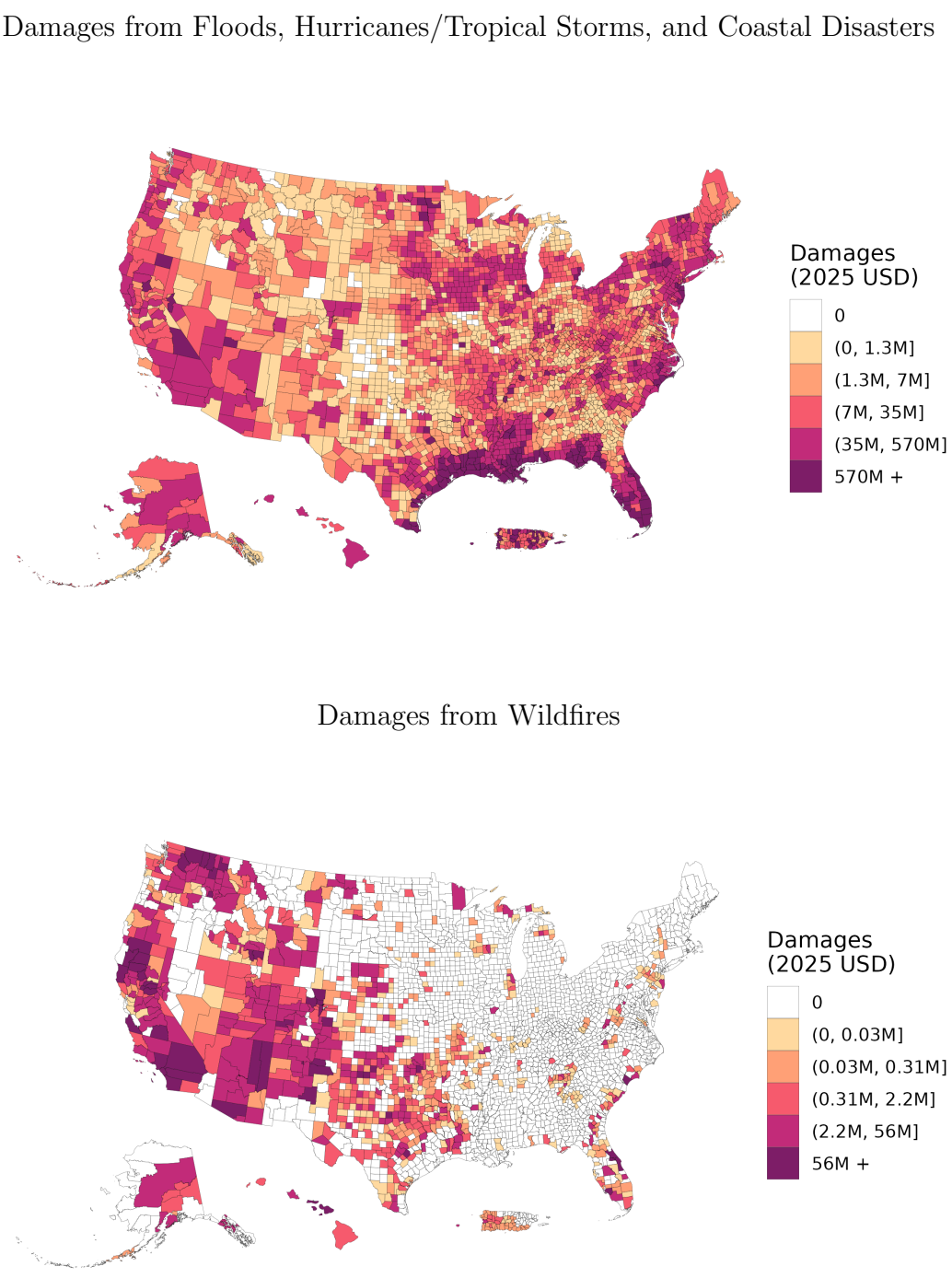


Figure 1: Total damages from flooding, hurricanes/tropical storms, coastal disasters, and wildfires from 1996 to 2025. This figure shows a heat map of total cumulative county-level damages from flooding, hurricanes/tropical storms, and coastal disasters (top panel) and wildfires (bottom panel) between 1996 and 2025. Table OA.2 provides definitions of each disaster type. Damages are inflation-adjusted to December 2025 USD using the CPI. Figure OA.2 shows damages from all disaster types and droughts. Sources: NOAA, U.S. Census Bureau.

Our main data source is the Storm Events Database (SED), an official NOAA publication. Since 1996, the SED has recorded significant or unusual weather phenomena in a national database. The SED reports direct property damage, crop damage, and direct and indirect fatalities and injuries. The location of each event is either a county or a zone, with zones designed to capture weather differences within a county due to, for example, elevation or proximity to large bodies of water.

Our analysis is structured in four steps. First, we describe our methodology for mapping all events to counties. We use historical maps to identify which county (or counties) each zone intersects. For zones that overlap multiple counties, we use Census block group data to construct 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. We use time-varying weights to construct a crosswalk from zones to counties. We build this mapping for current and historical vintages of NOAA's geographic units so the crosswalk is based on boundaries in effect at the time of the disaster.

Second, we document substantial differences across disaster types in severity, geographic concentration, damage composition, and the communities they affect. Wildfires cause the largest losses in affected counties (averaging around $1.5 billion), followed by coastal disasters and hurricanes. Wildfires also tend to be geographically concentrated, while other disasters such as droughts affect many more counties. Across local communities, wildfires tend to hit affluent counties, while droughts and winter weather disasters disproportionately affect lower-income areas. Finally, property losses account for most damage from wildfires, coastal disasters, and floods, whereas crop losses dominate drought damage and make up a substantial share of winter-weather losses.

Third, we show that household spending is highly resilient after natural disasters. Specifically, we merge *Losses from Natural Disaster* with data from Numerator, a consumer data company that maintains a large, nationally representative transaction-level dataset, to construct a county-day measure of in-store consumer spending from 2019 to 2025. Household spending increases modestly before hurricanes and coastal disasters, consistent with antici-

patory purchases, falls sharply at disaster onset, and returns to its pre-disaster level within a week. Winter weather produces a smaller decline and a slower recovery. We find no detectable contraction for other disaster types, including wildfires. Our weights also allow us to document heterogeneity in the spending response within a disaster: we find that counties bearing more of the damages from the same hurricane experience larger spending declines, a pattern that an even split across counties would mask.

Fourth, we show that this rapid recovery in spending masks persistent financial consequences for households with weaker credit profiles. This analysis uses the publicly available Federal Reserve Bank of Philadelphia Consumer Credit Explorer data, an anonymized, nationally representative panel covering about 1 in 20 U.S. individuals with a credit file and Social Security number. We find that the share of borrowers using more than 75% of their available revolving credit rises and remains elevated for several quarters after hurricanes, coastal disasters, and winter-weather disasters. These patterns suggest that households use revolving credit to smooth consumption after natural disasters, resulting in persistent financial strain for non-prime borrowers.

These applications show how researchers can use *Losses from Natural Disasters* to study the economic effects of extreme weather events. Because each disaster includes an onset date and county-level losses, the data can be merged with high-frequency measures of local economic activity and administrative and commercial datasets on households, firms, financial institutions, and governments.

Related literature. Our comprehensive dataset on damages, injuries, and fatalities from natural disasters contributes to the literature that uses local exposure to 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). Much of this literature relies on data from SHELDUS (a primarily subscription-based database that divides multi-county zone losses equally), FEMA disaster declarations (which excludes undeclared disasters), and NOAA's Billion-Dollar Weather and Climate Disasters

(which excludes smaller events and is no longer updated). Our database is publicly available, regularly updated, and constructed by allocating NOAA's meteorological-zone losses to counties using weights based on population, housing, and economic activity.

We also contribute to the literature on how local economies and households respond to shocks by documenting new facts about consumer spending and household financial strain around natural disasters. Existing work studies spending, household finances, and economic adjustment around individual disasters (e.g., Deryugina et al., 2018; Aladangady et al., 2016, 2022; Agarwal et al., 2024; Gallagher and Hartley, 2017; Bleemer and van der Klaauw, 2019; Billings et al., 2022; del Valle et al., 2024) or analyzes county-level economic outcomes at lower frequencies (e.g., Boustan et al., 2020; Roth Tran and Wilson, 2025).[3] Using high frequency spending data and MSA-level consumer credit data, we compare the magnitude and persistence of consumer spending responses and financial strain across a broad set of U.S. disasters. Our results suggest that consumer spending can recover quickly after a disaster even as household financial strain persists.[4]

Outline. The remainder of the paper is structured as follows. Section 2 presents our data. Section 3 discusses the incidence and damages of various types of disasters. Section 4 documents the evolution of consumer spending and households financial conditions around disasters. Section 5 concludes.

2 The *Losses from Natural Disasters* data

We now present our data. Section 2.1 describes our main data source. Section 2.2 explains how we construct our county-level estimates of losses from natural disasters. See Appendix A

[3]Related literature provides cross-country evidence on the effects of natural disasters and weather shocks on aggregate output, growth, and economic development (e.g., Noy, 2009; Cavallo et al., 2013; Hsiang and Jina, 2014; Dell et al., 2012) and examines how insurance markets allocate climate risk (e.g., Gruber and Solomon, forthcoming; Sastry et al., forthcoming).

[4]This interpretation relates to the consumption-smoothing literature, which emphasizes liquid wealth and borrowing as buffers against temporary shocks (e.g., Morduch, 1995).

for additional details.

2.1 The official data source

Our estimates come from the Storm Events Database (SED), a 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 National Weather Service (NWS) trained spotters, county, state, and federal emergency management officials, local law enforcement, and media reports.[5] 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.2 provides a complete list of the event types in the SED data. The table also categorizes 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.

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

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

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 indirect injury or fatality.

Location of natural disasters. The SED consistently documents disaster locations using geographic areas, a field populated for all observations. The geographic area type in the SED depends on the event type. As shown in Table OA.2, 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."[6] 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 a zone can intersect more than one county.

Importantly, events are defined to be zone-specific or county-specific. Hence, if the same natural disaster affects multiple zones or counties, the data features a separate event (i.e., a separate observation) for each affected zone or county. 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.

2.2 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 across counties using weights that reflect the spatial distribution of population, housing stock, and economic activity.

The data challenge with Public Forecast Zones. Zones allow for more accurate weather forecasts but 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 zone boundaries and identifiers (e.g., splitting one zone into two), but the correlation files contain mappings only for the most recent zone vintages. As a result, merging historical events with the current crosswalk leads to unmatched events and a potentially inaccurate mapping. Second, the crosswalks do not provide a rule for apportioning zone-level damages to counties when the zone spans multiple counties.

Given these issues, we construct our own crosswalks using zone and county maps. The

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

crosswalks link each zone to all counties it overlaps. For zones that overlap multiple counties, we calculate weights to allocate damages to counties based on the share of a zone's population, housing stock, or economic activity 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 NOAA zone vintage. Shapefiles are a data format that contains a collection of polygons oriented in space. Intersecting zones and counties generates a new map of smaller, mutually exclusive spatial subunits. Each subunit 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. For population, we then calculate the weights for each zone-county pair by dividing the zone-county pair's population by the zone's total population. 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 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.

Example: Zone 504 in Washington state. To make this procedure more concrete, Figure 2 shows crosswalk construction using zone 504 in Washington state from the 2017 vintage of zone boundaries. Panel A shows the zone overlaid on the Washington county map, and Panel B zooms in on the three counties the zone overlaps: Mason, Thurston, and Lewis. 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 with one observation for each zone-county pair.

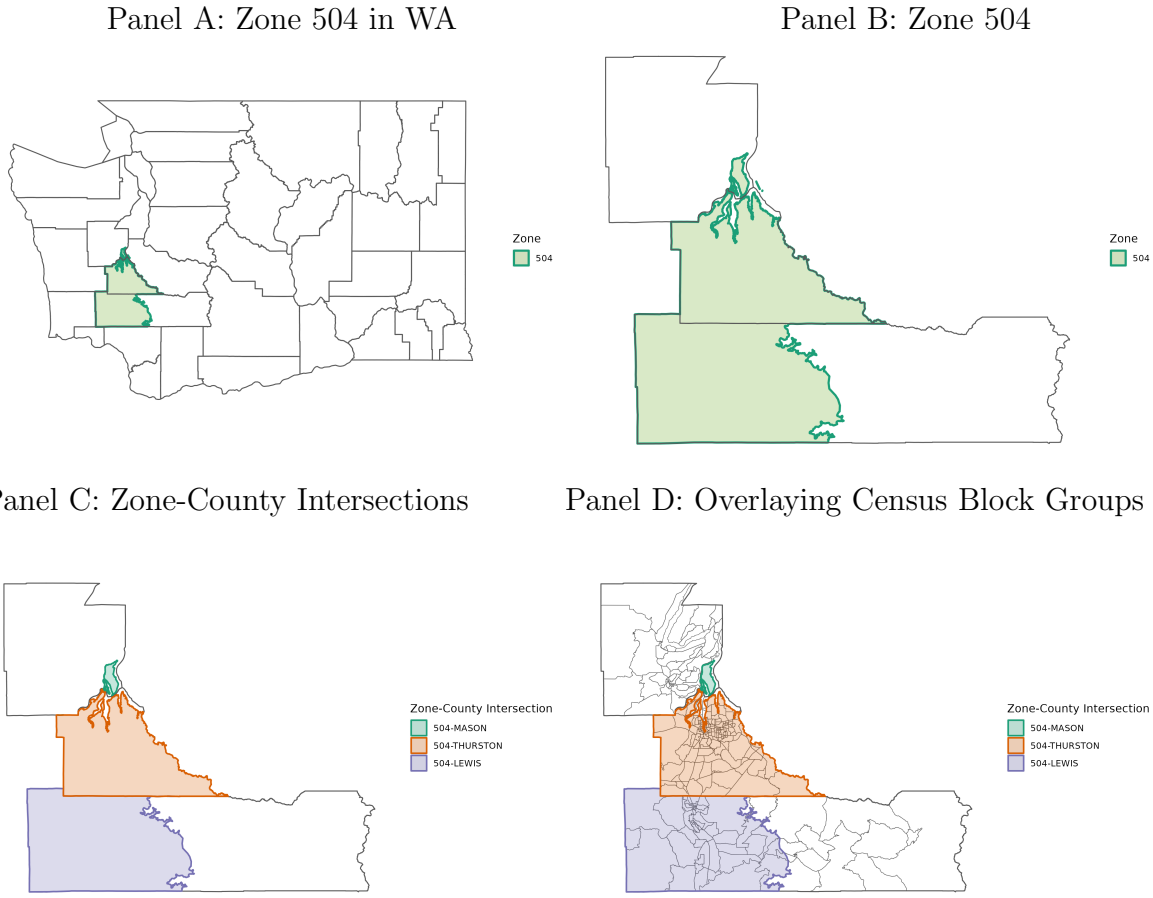


Figure 2: Example of crosswalk construction. This figure shows an example of crosswalk construction for zone 504 in Washington state. Panel A shows the zone overlaid onto the county map. Panel B zooms in on Mason, Thurston, and Lewis counties—the counties that overlap with zone 504. Panel C and Panel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

The three colored polygons in Panel C represent each observation in the spatial intersection.

Next, we construct weights that apportion damages from zone z to counties $c_1, \ldots, c_n$ ($n = 3$ in our example). 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. A naïve equally-weighted weighting scheme for each zone-county pair would simply be calculated as $1/n$.

We construct the weights by calculating 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. We cannot directly obtain values for the economic and demographic variables 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 is shown in Panel D of Figure 2, which overlays census block groups onto the zone-county subunits. We calculate 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 its equal weight (0.333) and area-based weight (0.404). This discrepancy is because this portion of Thurston County contains 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. We execute the process used in this example for each zone in all 50 states plus D.C. and Puerto Rico. We then append the crosswalks for each state to form a single crosswalk for each NOAA map, and we repeat this process for the 46 vintages of NOAA maps. As a final step, we merge all zone-level events with the crosswalk for the zone boundaries in effect at the time of the event. We append this data to the county-level events in the SED. We assign these events a weight of one for each of the six methodologies, since they occur in only one county.

The final dataset. Our final dataset is at the event level and 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. Appendix C shows that our 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.

3 Disasters and damages

We now exploit the precise event timing and county-level damages in our data to document the severity, geographic concentration, and damage composition across disaster types.

We find that wildfires, while geographically concentrated, tend to cause the largest losses in affected counties, followed by coastal disasters and hurricanes. Table 1 compares the ten most damaging episodes across each disaster type over 2001–2025. Wildfires are, on average, the most damaging, with mean county damages of roughly $1.5 billion, followed by coastal disasters at $1.1 billion and hurricanes at $742 million. Median damages tell a somewhat different story. Wildfires remain the most destructive by a wide margin, with median county damages of about $414 million, while hurricanes rank second at $59 million, and floods third at $31 million. The large gaps between means and medians, particularly for coastal events, floods, hail, and tornadoes, indicate that relatively few counties experience exceptionally large losses. The geographic reach of disasters also differs substantially. The ten largest drought episodes generate 335 county-disaster observations, compared with 196 for hurricanes and 148 for winter weather, whereas the ten largest wildfires affect only 25 county-disaster observations. In sum, wildfires are exceptionally costly where they occur, while droughts and several weather-related disasters are much more geographically dispersed.

Disasters also differ in the communities they hit and the damages they create. First, wildfires tend to hit affluent counties, with an average income per capita of approximately $46,000, while droughts and winter weather disasters affect lower-income areas more, with average incomes closer to $30,000–$32,000. The largest hail, thunderstorm/rain, and tsunami/seiche episodes occur in relatively populous counties. Together, these patterns suggest that disaster types differ not only in the magnitude and concentration of damages, but also in the types of local economies they affect. Second, property damage accounts for nearly all reported

			Damages ($ mil., inflation adjusted)							Mean County (K)	
Disaster Type	**County Obs.**	**Events**	**Mean**	**SD**	**P25**	**P50**	**P75**	**Prop.**	**Crop**	**Pop.**	**Income pc**
Wildfire	25	10	1,518.4	4,029.3	35.5	413.7	1,228.0	1,516.6	1.8	449	46
Coastal	124	10	1,058.9	3,689.7	3.0	21.7	156.3	1,056.0	2.9	203	37
Hurricane	196	10	742.1	1,910.2	5.3	58.7	556.1	716.9	25.2	133	34
Flood	122	10	707.5	2,170.8	1.4	30.6	269.9	707.2	0.3	176	42
Hail	34	10	505.1	972.0	0.0	0.4	711.1	501.0	4.1	693	44
Tornado	118	10	193.6	598.7	0.1	1.6	30.5	193.6	0.0	201	41
Wind	89	10	172.5	372.2	0.8	8.5	125.4	169.1	3.4	184	36
Winter Weather	148	10	61.0	127.2	1.0	15.1	75.7	26.0	35.0	150	30
Drought	335	10	47.4	163.2	20.3	22.4	36.1	4.3	43.1	33	32
Thunderstorm/Rain	58	10	23.6	45.9	2.7	13.9	25.9	12.5	11.1	799	35
Heat	104	10	8.1	35.8	0.2	0.2	1.0	0.4	7.8	151	40
Tsunami/Seiche	19	10	5.9	9.8	0.2	1.4	8.4	5.9	0.0	885	46

Table 1: Damages caused by the top-10 disasters by type, 2001–2025. The table reports damage statistics for the ten largest episodes within each disaster category over 2001–2025, ranked by total mean inflation-adjusted damages. Episode-level damages are allocated across affected counties using our data's population-weighting scheme, which assigns each affected county a share of total damages proportional to its population. P25, P50, and P75 denote the 25th, 50th, and 75th percentiles, respectively, of the resulting county-disaster damage distribution. We source county-level income, population, and GDP from the Bureau of Economic Analysis (BEA). Because 2025 county-level GDP data are not yet available, we carry forward 2024 BEA values to 2025 when constructing the county characteristics reported in the final columns.

losses from wildfires, coastal disasters, floods, hail, and tornadoes, whereas agricultural (crop) losses are substantially more important for droughts and winter weather. For droughts, mean crop losses of $43.1 million constitute the overwhelming majority of average damages, while property losses average only $4.3 million. Winter weather similarly exhibits a sizable crop component, with average crop damages of $35.0 million compared with $26.0 million in property damages.

4 Resilient consumer spending and financial strains

To illustrate one application of our data, we examine how major natural disasters affect local consumer spending (Section 4.1) and household financial conditions (Section 4.2), documenting a rapid recovery in spending alongside more persistent increases in credit card utilization among weaker borrowers.

Data on consumer spending and credit card utilization. To analyze the effect of disasters on local spending and household financial conditions, we merge the *Losses from Natural Disasters* data with transaction-level data on consumer spending and Metropolitan Statistical Area (MSA)-level data on consumer debt.

We measure consumer spending using data from Numerator, a consumer data company that maintains a large, nationally representative panel of over 150,000 U.S. households. Panelists are the primary shoppers in their households and must report at least two shopping trips per month for 12 consecutive months. Numerator collects transaction data through multiple channels, including physical receipts, digital and email receipts, and linked loyalty accounts.[7] The Numerator panel includes panelists from over 90% of U.S. residential zip codes, ensuring broad geographic coverage. Prior work has used Numerator consumer spending data to study aggregate retail spending (e.g., Hacıoğlu Hoke et al., 2024; Brave et al., 2024) and household shopping behavior (e.g., Levine and Hristakeva, 2026).[8] For our analysis, we aggregate basket-level expenditures over the 2019 to 2025 period by store location to construct a measure of daily consumer spending at the county level. We exclude online transactions and purchases that cannot be assigned to a physical store ZIP code.

We measure household financial strain using publicly available data from the Federal Reserve Bank of Philadelphia's Consumer Credit Explorer, which is based on the Federal Reserve Bank of New York's Consumer Credit Panel/Equifax (CCP) data (Federal Reserve Bank of Philadelphia, 2026). The CCP is an anonymized, nationally representative panel covering approximately one in 20 U.S. individuals with a credit file and Social Security number. In the public data, reported only quarterly at the MSA level, we observe changes in consumer credit use across regions over 2005–2025. Our primary outcome is the share of borrowers with positive credit card debt whose outstanding balance is at least 75% of their available credit limit.[9] We interpret this measure as a proxy for household financial strain, as borrowers with a high utilization rate have less remaining credit capacity to absorb unexpected expenses or income losses. We examine this measure separately for prime and non-prime borrowers, defined as consumers with Equifax Risk Scores greater than or equal

[7]This combination of continuous participation and multiple collection methods (including passive through digital capture methods) reduces concerns that observed spending changes around disasters simply reflect disruptions to receipt reporting. Moreover, panelists have up to two weeks to submit physical receipts.

[8]Notably, aggregate retail spending constructed from the Numerator panel closely tracks Census retail sales (Hacıoğlu Hoke et al., 2024).

[9]Credit card measures are based on general-purpose credit cards.

to 660 and below 660, respectively. Because these data are available at the MSA level, we aggregate disaster exposure to the MSA level when examining changes in household credit conditions.

4.1 Disasters and consumer spending

We now investigate the effects of various disaster types on local consumer spending. Prior work has documented that natural disasters can disrupt household spending in the context of a specific episode, namely Hurricane Katrina (e.g., Agarwal et al., 2024) and the 2015 Chennai flood (e.g., Gallagher and Hartley, 2017). In this section, we instead document the magnitude and persistence of consumer spending responses to *all* disaster types in the U.S.

To this end, we examine how local consumer spending evolves around major natural disasters using high-frequency transaction data from January 2019 through January 2026. We aggregate daily spending to the county level by store location and focus on the ten largest non-overlapping episodes of each disaster type from 2019 through 2025. For each episode, we examine a window from 14 days before to 20 days after the disaster start date. To isolate the response to a single shock, we exclude all county-episode observations in which the county experiences another top-ten disaster of a different type within the same window. With this procedure, we attribute observed changes in spending to a specific disaster type. We also remove overlapping episodes of the same type within a county.

Our high-frequency transaction data have two main advantages. First, they allow sharp identification of spending effects around disaster onset dates. By examining spending within a narrow window around each event, we can distinguish abrupt changes coinciding with the disaster from lower-frequency changes in local economic conditions. Second, assigning purchases geographically by store location lets us measure disasters' effects on economic activity within the affected area. Following a natural disaster, households may evacuate or temporarily shift purchases to neighboring counties. Using our store-location measure, these shifted purchases appear as a decline in spending within the affected county, even if the affected households continue spending elsewhere. In other words, our baseline estimates should be interpreted primarily as effects on consumer spending and activity at local businesses, rather than as changes in the total spending of affected residents.

We estimate the following event-study specification separately for each disaster type g:

$$\log(\text{Spending}_{c,e,t}) = \sum_{\substack{k=-14 \\ k\neq -10}}^{20} \beta_k^g \mathbb{1}\{\text{EventDay}_{e,t} = k\} + \gamma' X_{c,year(t)-1} + \alpha_c + \delta_{\text{weekday}(t)} + \varepsilon_{c,e,t},$$

where c denotes a county, e a specific disaster episode, and $\tau_{e,t}$ the days relative to the start date of the disaster. We normalize the event-study coefficients to ten days before the disaster to capture anticipatory spending before the onset of a disaster. Hence, β_k^g measures the change in log daily spending on day k relative to ten days prior. County fixed effects absorb persistent differences in spending across counties, while day-of-week fixed effects account for regular within-week spending patterns. We also control for lagged annual county GDP, population, and per-capita income, and cluster standard errors at the county level.

Figure 3 presents the estimation results, with each panel corresponding to a different disaster type. The figure documents substantial heterogeneity in the spending response across disaster types. Hurricanes and tropical storms generate the largest decline in spending, with total spending rising in the days immediately before the disaster, dropping sharply around its onset, and returning to approximately its pre-disaster level within a week. This pre-disaster increase in spending is consistent with households bringing purchases forward in anticipation of an impending disaster. Coastal events show a similar pattern, although the decline is shorter-lived and spending recovers quickly. Winter weather produces a smaller initial contraction but a notably longer recovery, along with a modest pre-event increase in spending. Tornadoes, floods, and wind events also exhibit slight pre-disaster increases followed by declines around disaster onset, though the magnitudes are considerably smaller. Interestingly, wildfires show little measurable effect on local spending despite ranking among the most damaging disaster categories in Table 1. Taken together, these results document that spending falls sharply at the onset of specific damaging disasters, but recovers quickly, even though the shortfall from the disaster period is not fully offset by above-normal spending during the recovery period (Aladangady et al., 2022).

The rapid rebound in local consumer spending across disasters is notable. Given that disasters can disrupt employment, housing, and local infrastructure, one might expect household spending to remain depressed well beyond the immediate aftermath. Instead,

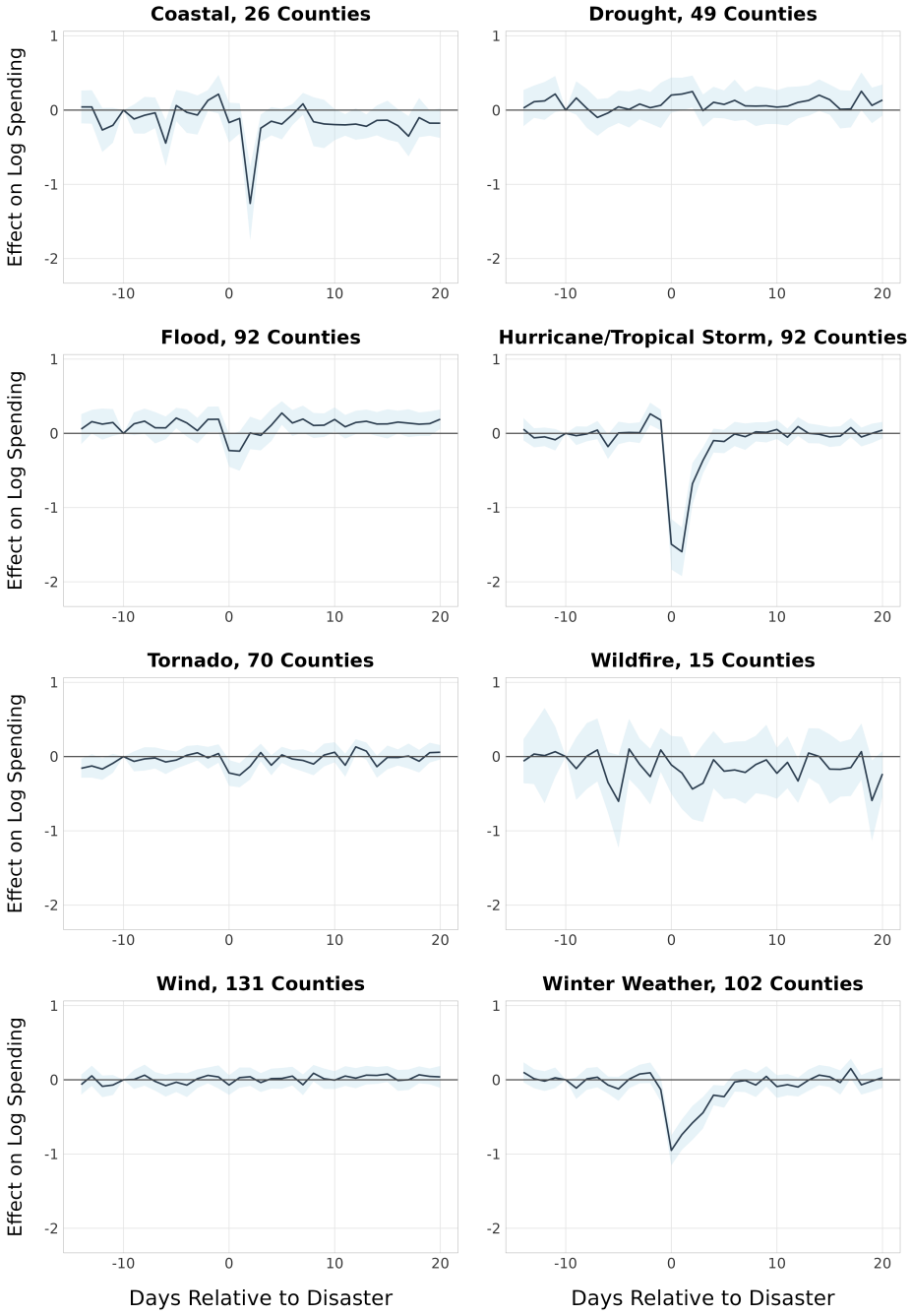


Figure 3: The effect of the top-10 most damaging disasters on consumer spending. The figure reports event-study estimates of the effect of major natural disasters on log daily consumer spending. Spending is aggregated to the county-day level based on store location. For each disaster type, the sample includes up to the ten largest non-overlapping episodes from 2019 to 2025, and a window from 14 days before to 20 days after disaster onset. Day −10 is the omitted reference period. County-episode observations exposed to another top-ten disaster within the event window are excluded. All specifications include county and day-of-week fixed effects and controls for lagged county GDP, population, and per-capita income. Standard errors are clustered at the county level. Shaded areas denote 95% confidence intervals. Source: Household panel from Numerator.

despite substantial differences in the magnitude of the initial response, none of the disaster types produces a sustained decline in local spending over the subsequent weeks, pointing to considerable resilience in short-run local economic activity. The spending exercise illustrates why our weighting schemes matter for disasters affecting multiple counties: under each of our alternative weighting schemes, counties assigned larger damages within the same hurricane tend to experience larger spending declines (Table OA.4). Equal allocation cannot capture this relationship because it assigns identical damages to these counties.

One potential concern is that households facing a major disruption may temporarily become less likely to report purchases, mechanically generating an apparent decline in measured spending. Several features of the Numerator data help mitigate this concern. First, Numerator requires sustained panel participation and collects transactions through multiple channels, including physical receipts, email receipts, and linked loyalty accounts, so measurement does not depend exclusively on households manually submitting purchases. Second, a general decline in reporting following disasters would be difficult to reconcile with the substantial heterogeneity we observe across disaster types.

As a robustness check, we repeat the analysis by assigning purchases to consumers' home ZIP codes. This specification captures spending by affected residents even when they make purchases outside the disaster area, allowing us to distinguish a decline in household spending from a geographic reallocation of purchases. Second, this specification includes online transactions, which are not tied to a retailer's physical location and may therefore be less sensitive to disruptions in in-person shopping or receipt collection. The resulting responses, shown in Figure OA.3, are qualitatively similar but slightly smaller in magnitude, consistent with affected households partially reallocating purchases to stores outside the disaster area.[10]

[10]This specification relies on static consumer location information at the end of 2025 rather than the consumer's home location when the transaction occurred. If households move over time, particularly around disaster events, measurement error in home ZIP code assignment may also contribute to the smaller estimates.

4.2 Disasters and household debt

We now show that the rapid recovery in local consumer spending is associated with persistent financial consequences for borrowers with weaker credit profiles.

Because households might need to borrow to maintain spending during natural disasters, we next examine consumer debt using quarterly Federal Reserve Bank of New York Consumer Credit Panel data. Although available only quarterly and at the MSA level, the data span 2005–2025, allowing wider event windows while retaining a sample of large, non-overlapping disasters. We aggregate both disaster exposure and local economic controls to the MSA level and, again, select the ten largest non-overlapping disasters of each type based on MSA-level damages. We then estimate analogous quarterly event studies around each disaster, including MSA and quarter-of-year fixed effects as well as controls for lagged local economic conditions. We compare responses across prime and non-prime borrowers to assess whether post-disaster financial strain is concentrated among borrowers with weaker credit profiles.

The estimated coefficients in Figure 4 suggest that the rapid recovery in local consumer spending coincides with more persistent pressure on household balance sheets, particularly among borrowers with weaker credit profiles. More specifically, the figure examines the share of credit card holders using more than 75% of their available credit limit. Following hurricanes and tropical storms, coastal events, and winter weather disasters, the share of high-utilization cardholders rises more noticeably among non-prime borrowers than among prime borrowers and remains elevated for several quarters. This pattern is consistent with borrowers with weaker credit profiles relying more heavily on available revolving credit following major disasters, even as local consumer spending recovers relatively quickly. The estimates for other disaster types are generally smaller. We do observe differences in high utilization between prime and non-prime borrowers prior to disaster onset, however, so we interpret the larger post-disaster increase among non-prime borrowers as suggestive of heterogeneous effects rather than as a clean causal estimate of differential responses across credit-score groups.

Figure 4 also shows a decline in credit card utilization among non-prime borrowers following tornadoes. Because many of the most damaging tornado episodes in our full sample occur in the years following the Global Financial Crisis, this pattern may partly reflect

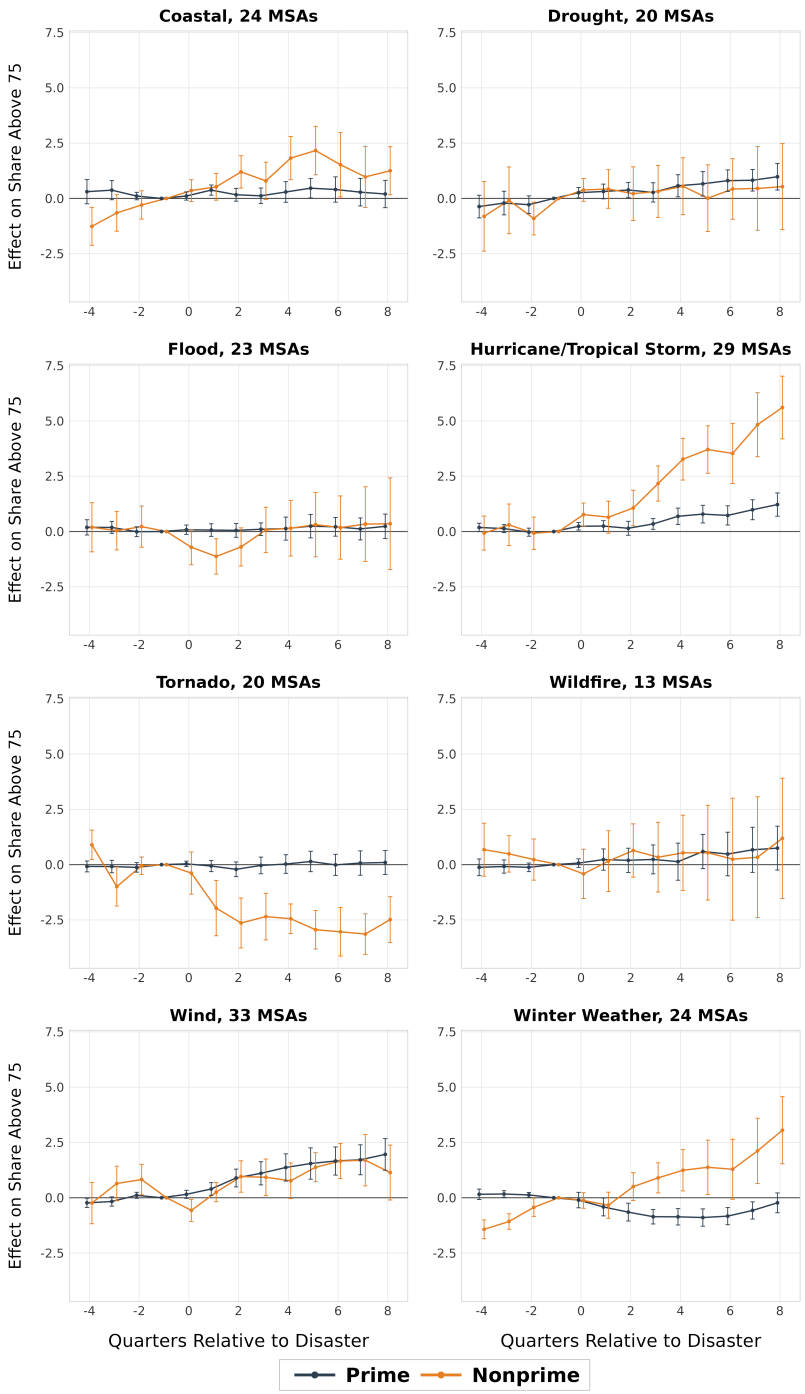


Figure 4: The effect of the top-10 most damaging disasters on credit card utilization. The figure reports event-study estimates of the effect of major natural disasters on the share of credit card holders using more than 75% of their available credit limit, separately for prime (blue) and non-prime (orange) consumers. Prime consumers have an Equifax Risk Score of at least 660. Non-prime consumers have a Risk Score below 660. For each disaster type, the sample includes the ten largest non-overlapping episodes based on MSA-level damages. Consumer-credit outcomes are measured at the MSA-quarter level. Quarter −1 is the omitted reference period. All specifications include MSA and quarter-of-year fixed effects and controls for lagged MSA GDP, population, and per-capita income. Standard errors are clustered at the MSA level; error bars denote 95% confidence intervals. *Sources:* Federal Reserve Bank of New York Consumer Credit Panel/Equifax Data and Federal Financial Institutions Examination Council Census Flat File, accessed via the Federal Reserve Bank of Philadelphia Consumer Credit Explorer.

broader post-crisis deleveraging rather than a disaster-specific response. As a robustness exercise, we re-estimate the specification using only disasters occurring post-GFC from 2014 to 2025, with results shown in Figure OA.4. Over this shorter sample period, tornadoes are no longer associated with lower card utilization. In contrast, hurricanes and tropical storms, coastal events, and, in this period, floods and droughts, are associated with higher utilization among non-prime borrowers.

A separate concern is that borrower risk scores may themselves respond to changes in household financial conditions following a disaster. We therefore also examine utilization by neighborhood income, comparing consumers in low- and moderate-income census tracts with those in middle- and high- income tracts. Being based on neighborhood income rather than borrowers' post-disaster credit outcomes, this classification provides an alternative measure of financial vulnerability. The results, shown in Figure OA.5, are qualitatively similar. Hurricanes and coastal events are associated with larger increases in high utilization among consumers in lower-income areas, while floods and droughts appear to raise utilization across both groups.

5 Conclusion

We introduce *Losses from Natural Disasters*—new publicly available, comprehensive data on county-level damages, injuries, and fatalities from natural disasters in the U.S. The data draws on official NOAA damage estimates and maps them to the county level using the spatial distribution of population, employment, income, and housing stock. Merging *Losses from Natural Disasters* with transaction and credit data, we document that (i) local consumer spending falls sharply at the onset of hurricanes and coastal disasters but recovers within a week, with no detectable response to wildfires, and (ii) the share of non-prime borrowers with high credit card utilization rises and remains elevated for several quarters.

Our goal is to provide the public with comprehensive, 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. *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, how we build the crosswalks, and how we allocate damages to counties. Appendix B presents additional tables and figures. Appendix C shows that our methodology yields estimates that are particularly accurate for severe disasters.

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. Data preparers collect, compare, and verify these disparate records at the 123 NWS Weather Forecast Offices (WFOs). If 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 tabulates the number and percent of NOAA events between 1996 and December 2025 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
NOAA/NWS	803,982	45.15
Other Government Official	362,780	20.37
Public	204,853	11.50
Media Report	154,863	8.70
Other Company	9,494	0.53
Other	131,162	7.37
Unknown/Missing	113,596	6.38

Table OA.1: 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 December 2025, together with the number of observations associated with each data source. Source: NOAA.

After verification, WFOs send data files to 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., 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.2 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: coastal disaster, winter weather, wind, flood, drought, wildfire, tornado, hail, heat, hurricane/tropical storm, thunderstorm/rain, tsunami/seiche, and other.

The SED contains several variables that allow researchers to identify the geographic areas impacted by the event, the start/end time of its occurrence, its magnitude, and resulting damages.

Location. 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 event types are designated for marine zones, which do not occur over land and are not

[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 and then converted it to CSV. 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.2: 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.

included in *Losses from Natural Disasters*. The geographic designator for each event type is reported in Table OA.2.

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 a zone can intersect 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, these variables are limited because they are missing for 42% of 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." Property damage refers to damage inflicted to private property as well as public infrastructure and facilities. Estimates are reported in nominal USD and are rounded to three significant digits followed by the magnitude of the value (i.e., \$1.55 billion 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, losses are recorded as crop damage if the vegetation was intended for harvest, 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 from physical destruction) but do not account for other indirect losses that occur after the event and are not realized as physical destruction. For example, a tornado-caused ruptured power line that falls on a home is easily observed and represents a direct physical loss to property. However, this event may also have indirect costs, such as business closures due to a lack of power. 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 preparers are instructed not to include these indirect costs in the reported property and crop damages.

Beyond damages, the SED also records direct and indirect fatalities and injuries. Data 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 has an episode identification code, and each episode typically includes multiple events. Episodes are broader classifications of phenomena that 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.

Events are defined for a single county (or zone) and are assigned a single event type from Table OA.2. NOAA uses the episode identifier to account for disasters that cover a large geographic area, cause events of different types, and link the individual events. The occurrence of multiple events under a single episode arises when a storm system (episode) impacts multiple counties (or zones), resulting in event-level observations for each county.[2] 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 as state- and WFO-specific, so 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). The New Orleans episode for Hurricane Katrina includes 27 individual events, one for each impacted zone.

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 downloaded shapefiles for two sets of geographies: the NWS Public Forecast Zones (zones) and U.S. Census administrative geographies (counties and block

[2]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.

groups). Shapefiles are a special data format for maps, representing a collection of polygons oriented in space. Geographic Information Systems (GIS) software 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. You can download current shapefiles 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 2025. 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 appears three times in the dataset, once for each county intersection. The most recent versions of the crosswalks can be downloaded from the NWS website. As discussed in Section A.3, these crosswalks are limited in availability and usefulness for allocating zone-level damages to the county level. Hence, we construct our own crosswalks and use NOAA-provided crosswalks to verify ours.

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.

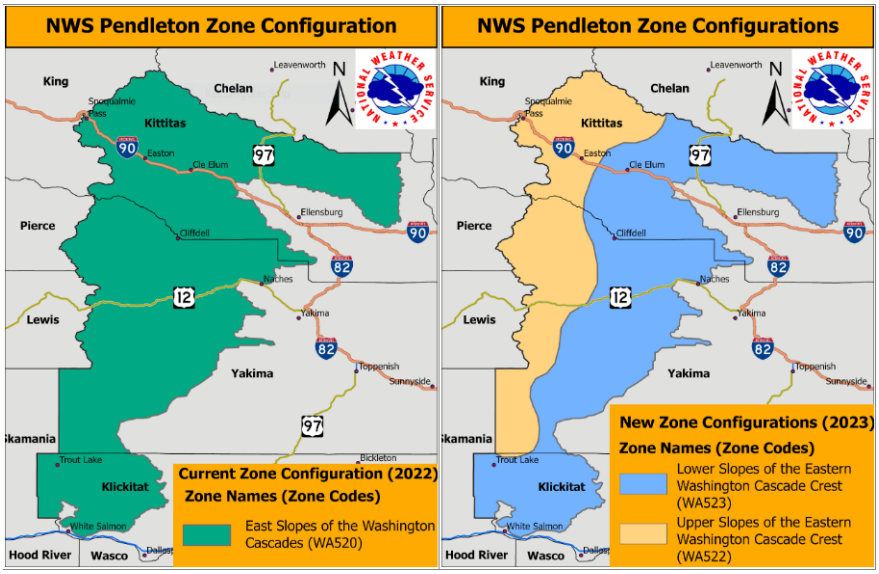


Figure OA.1: Public Forecast Zone change in Washington state.

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 2025, several storm events were reported in zone 520 of Washington state. However, the current zone-county crosswalk has no zone 520 in Washington state, 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, NOAA's website does not provide the full history of zone-county crosswalks. After contacting NOAA, their staff provided 18 zone-county crosswalks covering November 2015 to the present, leaving crosswalks missing from 1995 to October 2015.

Not only do the crosswalks not cover the entire history of the SED, but they are also limited in their usefulness for the second step of mapping 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 counties A and B, but it does not provide guidance on how to allocate damages between the two counties.

Given the limited availability and limited usefulness of NOAA's zone-county correlation files, we construct our own crosswalks using zone and county maps. The crosswalks link each zone to all counties it overlaps, completing 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 disaster damages in multi-county zones, completing the second step.

We construct these crosswalks for current and historical zone vintages (if the map is available), so events can be merged with crosswalks valid at the time of the disaster. After constructing the crosswalks and merging them with the SED, we can use the shares to allocate damages from the zone level to the county level. We now describe how to construct the crosswalks and link them to 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 a single county, this process is trivial, as all of the zone's damages can be allocated to that county. However, when a zone overlaps multiple counties, we need to choose weights that distribute the zone's damages across the counties it intersects.

Our methodology is flexible and allows us to construct weights that distribute damages proportional to 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 zone and county maps using a Geographic Information System (GIS) through the R package sf. The two maps cover the same territory but partition it differently. The intersection of the two maps generates a new map of smaller, 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 Washington State example in Figure

2, which plots the 2017 NOAA zone 504 boundaries 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). As discussed in the main body, the first step is to spatially intersect the zone with county boundaries. This process generates a dataset with one observation per 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 the 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 of 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 affected 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 need only the area of each zone-county pair, which we can calculate from the intersection shapefile using GIS software. We cannot directly obtain values for the economic and demographic variables 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. Panel D of Figure 2 shows the procedure for obtaining these estimates by overlaying 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

		Weighting Method					
Zone	**County**	**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.3: 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.

entire block group before summing to the zone-county level.[3] 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.

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 crosswalk for each of the 46 zone vintages for which we were able to obtain shapefile maps. Because maps prior to June 2006 are not available, we use the June 2006 zone map 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. For example, consider the vintage 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.[4]

Merging the SED crosswalks. The next step in constructing our dataset is to merge the set of all events in the SED 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

[3]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 come from the Decennial Census.

[4]We are able to obtain ACS 5-year data at the block group-level for each year between 2010 and 2025. 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 decennial 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.

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 the 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 in the effective map. This may be particularly important for events that occur shortly after NOAA updates the zone map.

(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 when 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, we match 99.7% of the total zone-level events. 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 not matched by this algorithm to NOAA zones. We successfully manually match 1,641 of these events, leaving 421 events that we cannot map to the county level.

After merging the crosswalks with the zone-level events, we append this data to NOAA county-level events. We assign these events 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 tables and figures

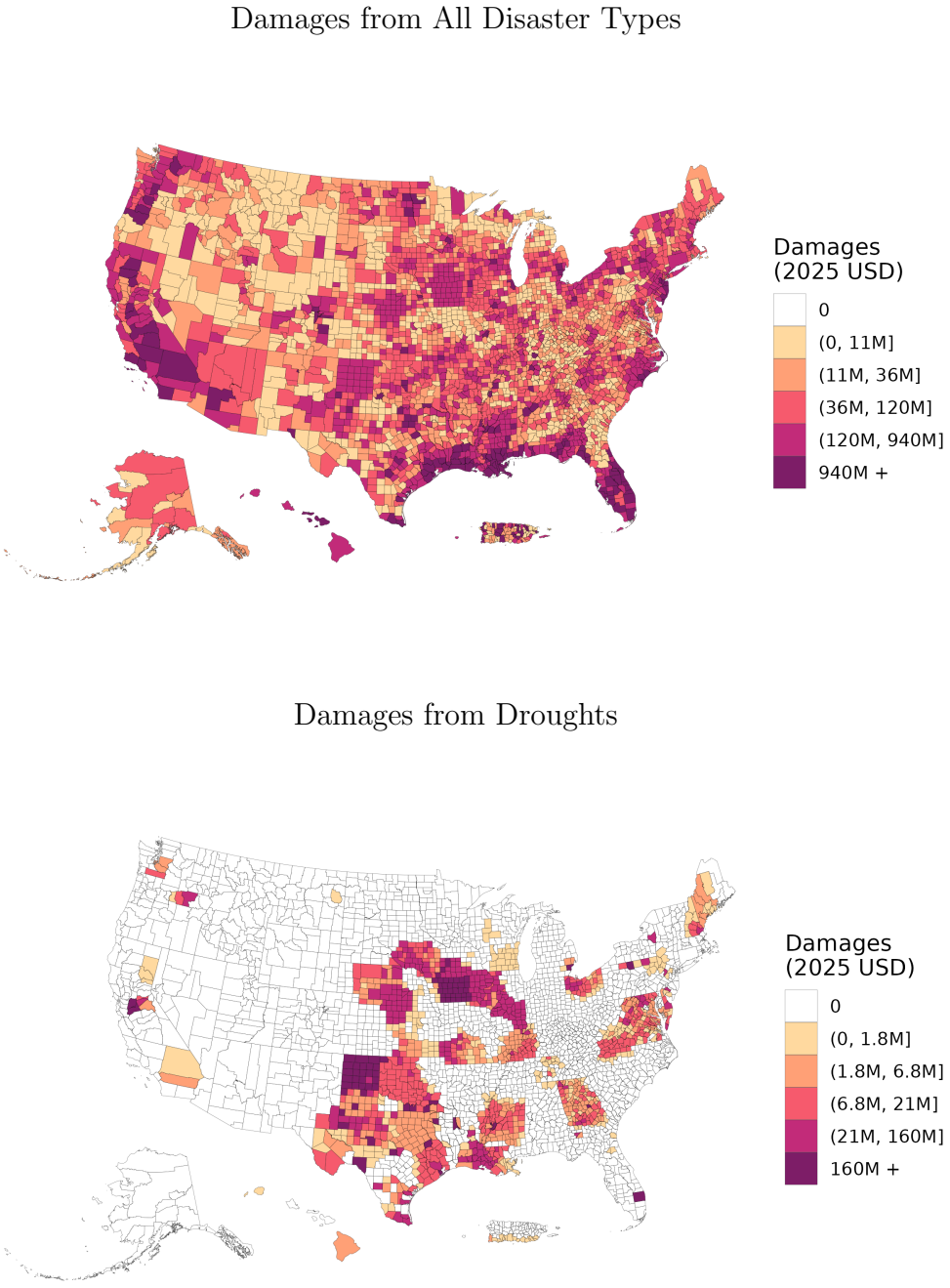


Figure OA.2: Total damages from all disasters and droughts from 1996 to 2025. This figure shows a heat map of total cumulative county-level damages from all disaster types (top panel) and droughts (bottom panel) between 1996 and 2025. Damages are inflation-adjusted to December 2025 USD using the CPI. Sources: NOAA, U.S. Census Bureau.

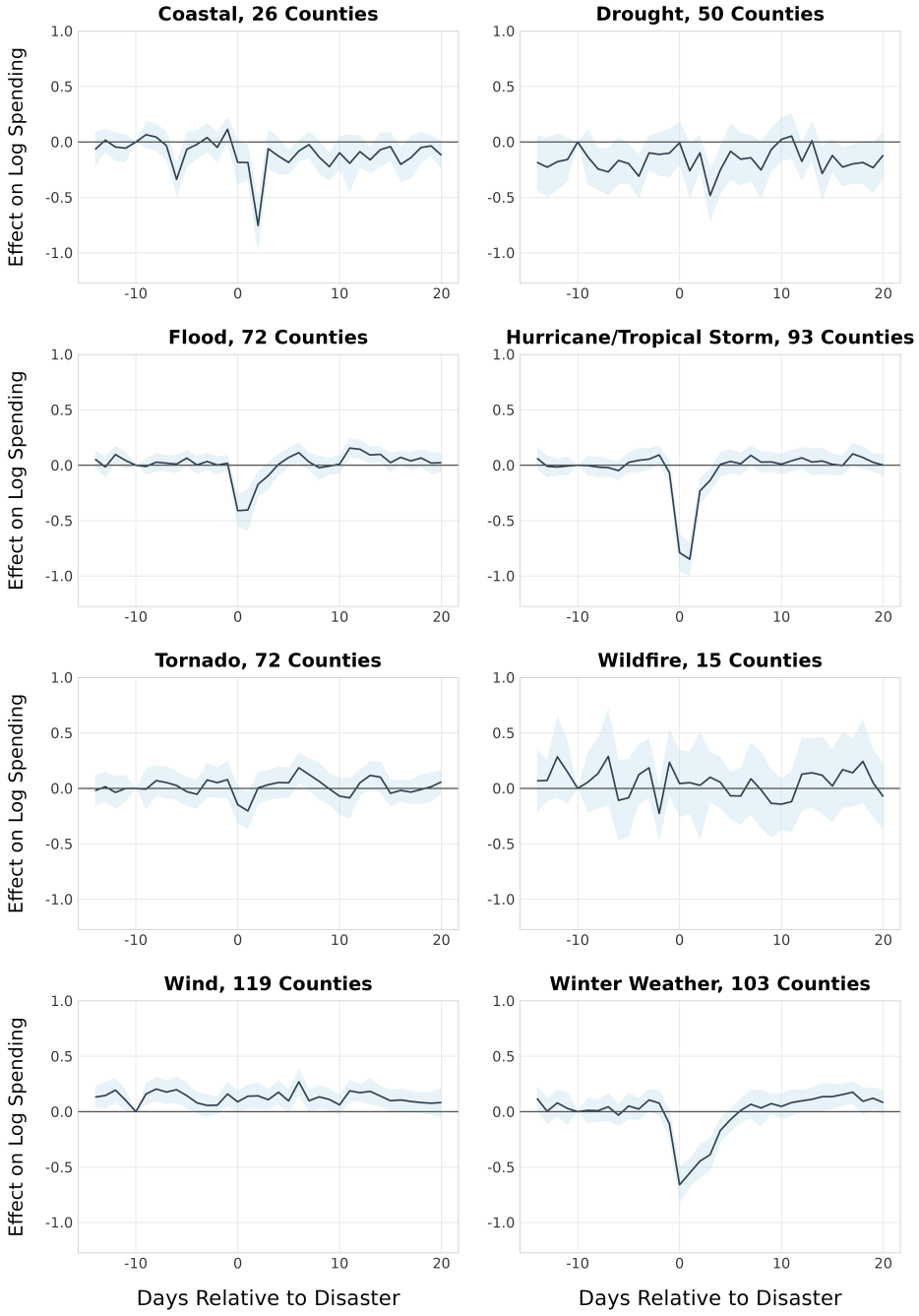


Figure OA.3: The effect of the top-10 most damaging disasters on consumer spending (effects based on consumers' location). The figure reports event-study estimates of the effect of major natural disasters on log daily consumer spending. Spending is aggregated to the county-day level based on the consumer's location rather than the store's location. The sample includes all observed transactions, including both in-store and non-store purchases. For each disaster type, the sample includes up to the ten largest non-overlapping episodes from 2019 to 2025, and a window from 14 days before to 20 days after disaster onset. Day −10 is the omitted reference period. County-episode observations exposed to another top-ten disaster within the event window are excluded. All specifications include county and day-of-week fixed effects and controls for lagged county GDP, population, and per-capita income. Standard errors are clustered at the county level. Shaded areas denote 95% confidence intervals. Source: Household panel from Numerator.

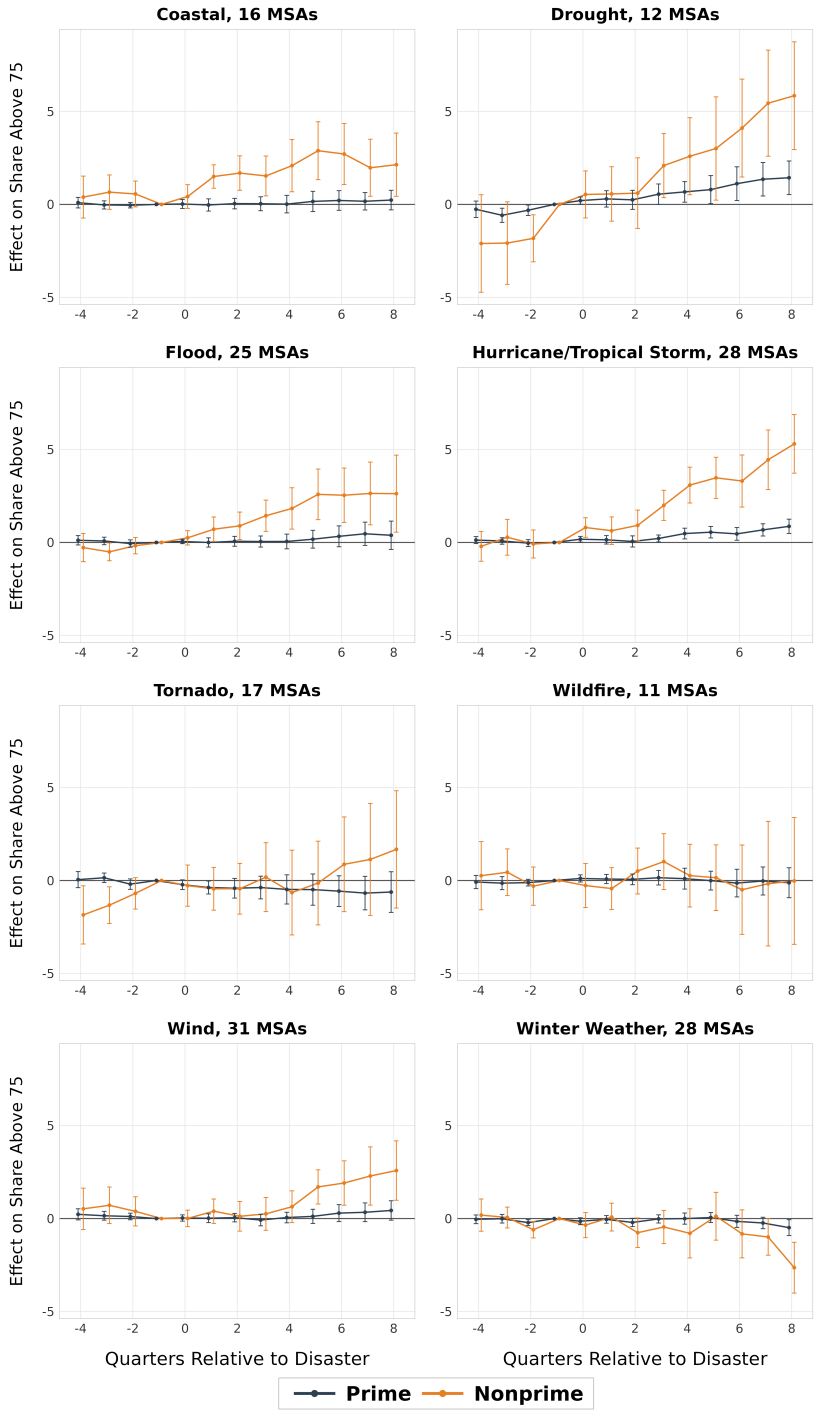


Figure OA.4: The effect of the top-10 most damaging disasters on credit card utilization, 2014–2024. The figure reports event-study estimates of the effect of major natural disasters occuring between 2014 and 2024 on the share of credit card holders using more than 75% of their available credit limit, separately for prime (blue) and non-prime (orange) consumers. Prime consumers have an Equifax Risk Score of at least 660. Non-prime consumers have a Risk Score below 660. For each disaster type, the sample includes the ten largest non-overlapping episodes based on MSA-level damages. Consumer-credit outcomes are measured at the MSA-quarter level. Quarter −1 is the omitted reference period. All specifications include MSA and quarter-of-year fixed effects and controls for lagged MSA GDP, population, and per-capita income. Standard errors are clustered at the MSA level; error bars denote 95% confidence intervals. *Sources:* Federal Reserve Bank of New York Consumer Credit Panel/Equifax Data and Federal Financial Institutions Examination Council Census Flat File, accessed via the Federal Reserve Bank of Philadelphia Consumer Credit Explorer.

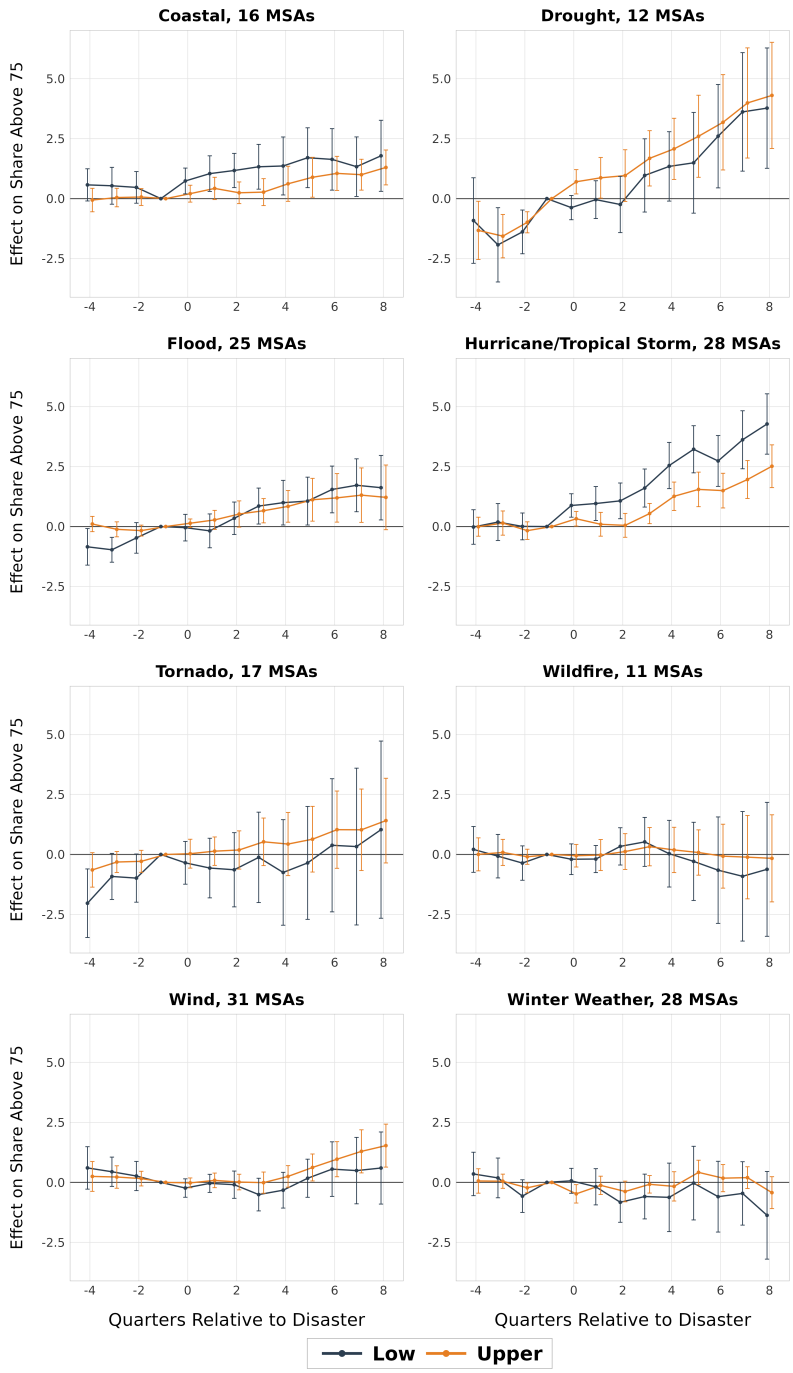


Figure OA.5: The effect of the top-10 most damaging disasters on credit card utilization by income group, 2014–2024. The figure reports event-study estimates of the effect of major natural disasters occuring between 2014 and 2024 on the share of credit card holders using more than 75% of their available credit limit, separately for low-and moderate-income (blue) and middle-and upper-income (orange) consumers. Low-and moderate-income refers to consumers residing in census tracts in which the median family income (MFI) is less than 80% of the MFI in the associated MSA, middle-and upper-income refers to consumers residing in tracts in which the MFI is greater than or equal to 80% of the MFI in the associated MSA. For each disaster type, the sample includes the ten largest non-overlapping episodes based on MSA-level damages. Consumer-credit outcomes are measured at the MSA-quarter level. Quarter −1 is the omitted reference period. All specifications include MSA and quarter-of-year fixed effects and controls for lagged MSA GDP, population, and per-capita income. Standard errors are clustered at the MSA level; error bars denote 95% confidence intervals. *Sources:* Federal Reserve Bank of New York Consumer Credit Panel/Equifax Data and Federal Financial Institutions Examination Council Census Flat File, accessed via the Federal Reserve Bank of Philadelphia Consumer Credit Explorer.

C 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 our data's accuracy increases with disaster severity.

Hurricane Katrina and the 2017–2023 Western Wildfires. We start with the 2017–2023 Western Wildfires and Hurricane Katrina, two disaster types (wildfires and hurricanes) that NOAA reports at the zone level. The literature has widely studied these episodes. 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 OA.6 shows that damages estimated using population-based weights differ substantially from damages estimated using equal weights. The left panel shows county-level wildfire damages in Washington, Oregon, and California from 2017 to 2023, with the black

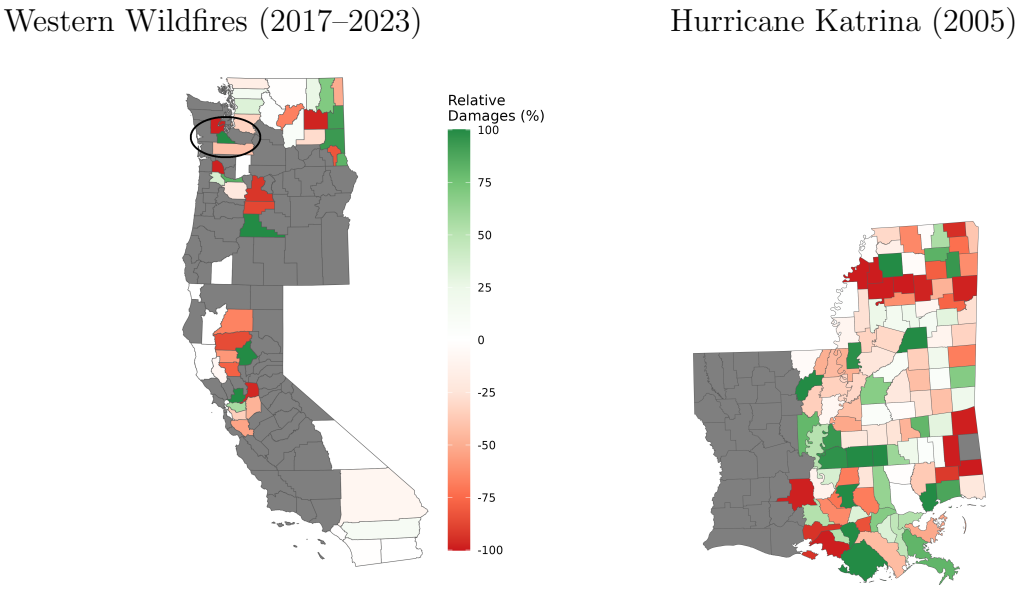


Figure OA.6: Population-weighted relative to equal-weighted damages: 2017–2023 Western Wildfires and Hurricane Katrina. This figure plots the relative difference between population-weighted and equal-weighted damages for the 2017–2023 Western Wildfires in Washington, Oregon, and California (left panel) 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.2 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.

circle highlighting Lewis, Mason, and Thurston counties from our example in Section 3. The colors indicate the difference between population and equal-weighted damages, highlighting how equal weights may under- or overestimate damages compared to population-based weights (green for underestimation, red for overestimation). The right panel also documents substantial deviations for Hurricane Katrina in Mississippi and Louisiana.

Accuracy of estimates increasing in disaster severity. We now compare estimates obtained using equal weights with those using weights based on the population distribution.

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

$$d_{ec}^{Population|Equal} = \frac{\text{Population Weighted Damages}_{ec} - \text{Equal Weighted Damages}_{ec}}{\text{Equal Weighted Damages}_{ec}}. \quad \text{(OA.2)}$$

Figure OA.7 to Figure OA.11 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. The differences are concentrated in the Mountain and Pacific West. Differences are smaller in the Midwest and on the East Coast. Figure OA.12 shows a binscatter plot of episode-county-level observations, with relative distance (absolute values on the y-axis) and episode loss severity (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 disaster severity, suggesting that our data are particularly accurate for severe disasters.[5] 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]The distance 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 over to comparisons with equal weighting and weights based on area, employment, income, or housing stock.

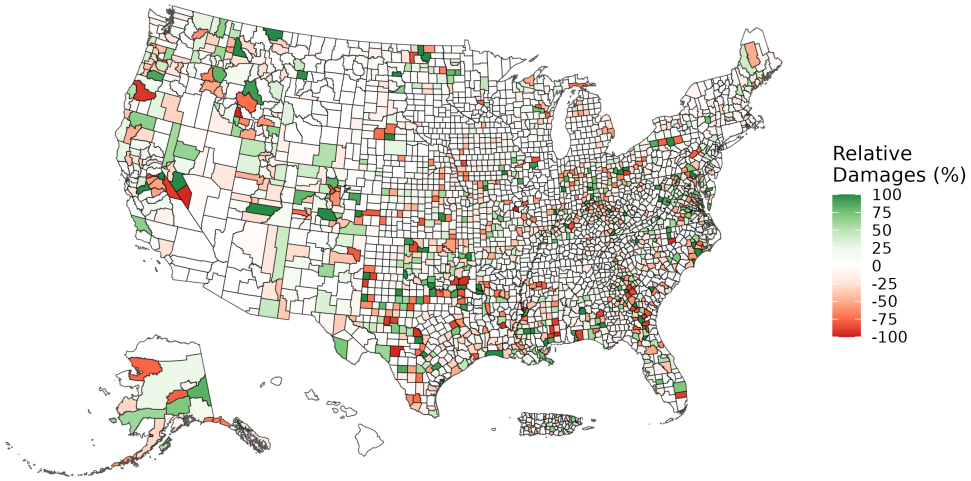


Figure OA.7: Area-weighted damages relative to equal: 1996–2025. This figure plots the relative difference between area-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2025. The relative distance metric is defined in equation (OA.2). Sources: NOAA, U.S. Census Bureau.

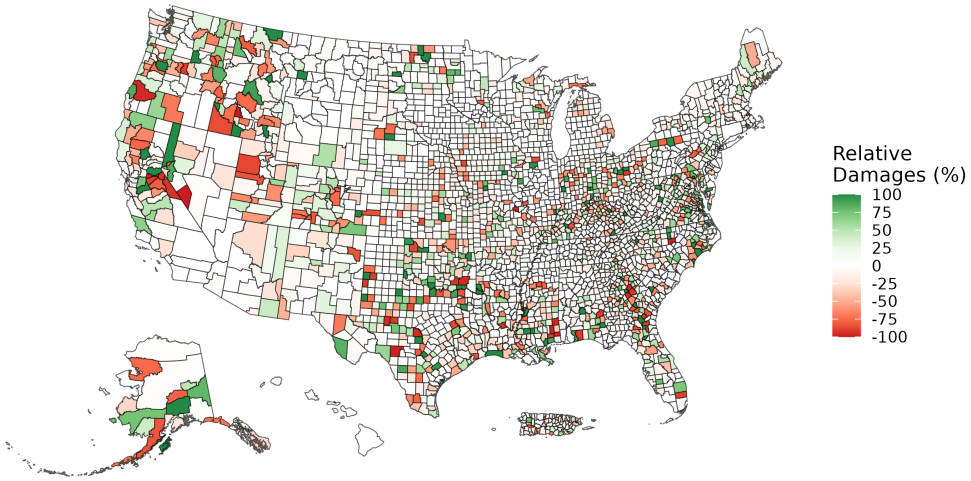


Figure OA.8: Population-weighted damages relative to equal: 1996–2025. This figure plots the relative difference between population-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2025. The relative distance metric is defined in equation (OA.2). Sources: NOAA, U.S. Census Bureau.

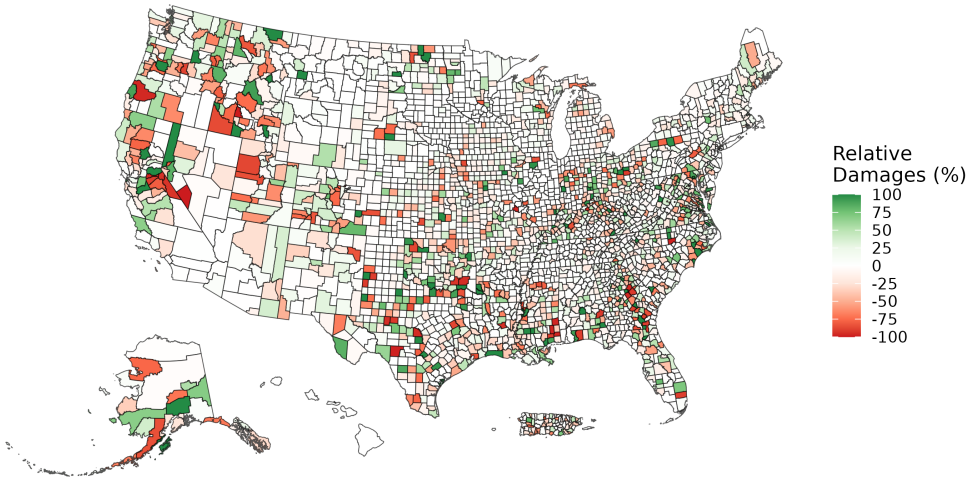


Figure OA.9: Employment-weighted damages relative to equal: 1996–2025. This figure plots the relative difference between employment-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2025. The relative distance metric is defined in equation (OA.2). Sources: NOAA, U.S. Census Bureau.

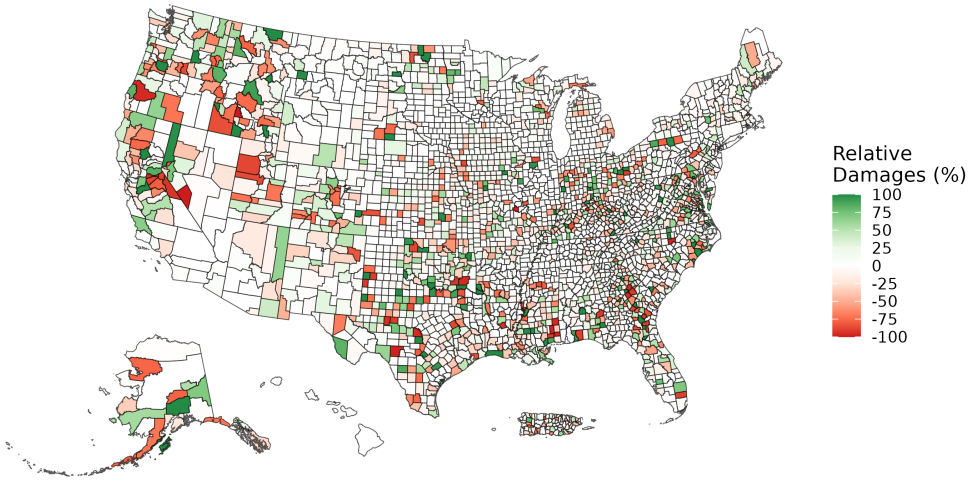


Figure OA.10: Housing stock-weighted damages relative to equal: 1996–2025. This figure plots the relative difference between housing stock-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2025. The relative distance metric is defined in equation (OA.2). Sources: NOAA, U.S. Census Bureau.

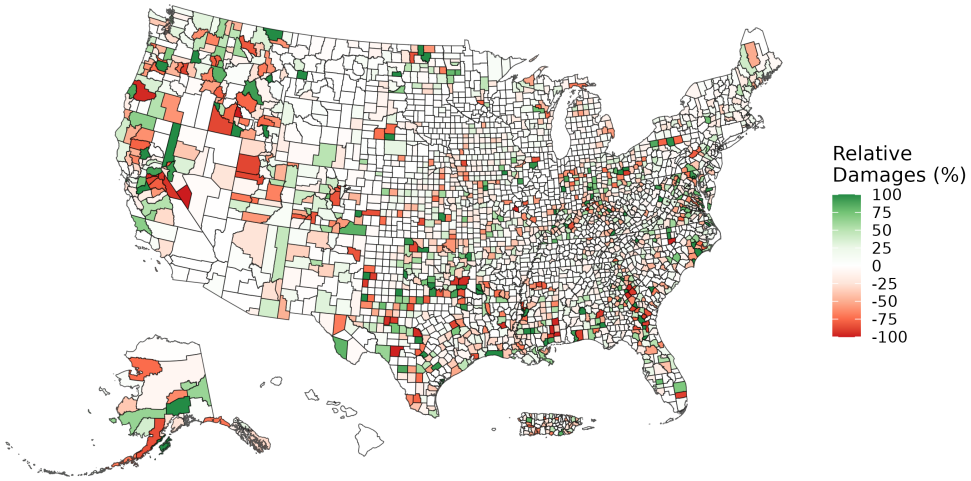


Figure OA.11: Income-weighted damages relative to equal: 1996–2025. This figure plots the relative difference between income-weighted damages and equal-weighted damages for all disasters that occurred between 1996 and 2025. The relative distance metric is defined in equation (OA.2). Sources: NOAA, U.S. Census Bureau.

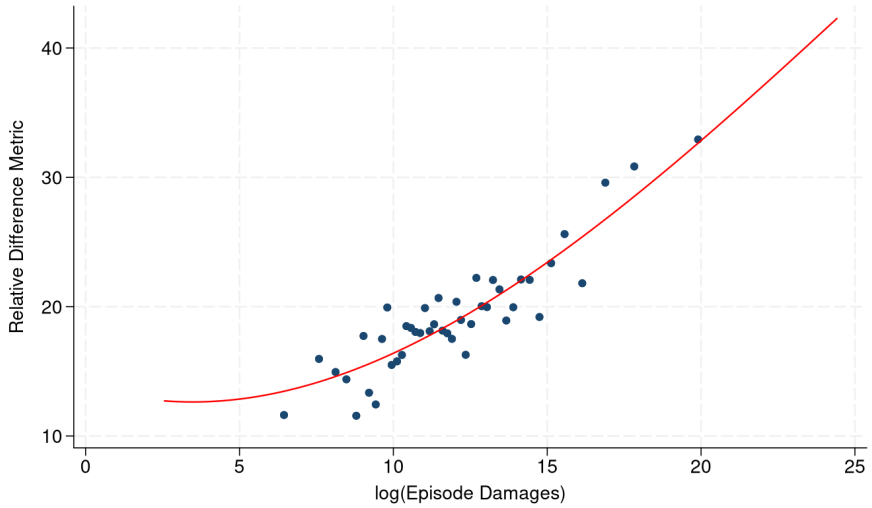


Figure OA.12: Absolute relative difference increasing in disaster size. This figure shows a binscatter plot using the methodology of Cattaneo et al. (2024). The y-axis shows the absolute value of the relative distance metric, and the x-axis shows episode-level population-weighted damages. The sample includes all episode-county observations with non-zero damages from 1996 to 2025. The absolute relative distance metric between population- and equal-weighted damages is defined in (OA.2). Sources: NOAA, U.S. Census Bureau.

	Hurricane		Wildfire	
Weighting Scheme	r	t-test p	r	t-test p
Population	-0.298^{**}	0.021	0.153	0.163
Area	-0.304^{**}	0.018	0.072	0.529
Employment	-0.298^{**}	0.021	0.179	0.105
Housing	-0.298^{**}	0.021	0.201^{*}	0.061
Income	-0.299^{**}	0.020	0.146	0.183

Table OA.4: Within-event correlation between disaster damages and changes in consumer spending, by weighting scheme: Top 50 multi-county hurricane and wildfire events, 2019–2025. This table shows the within-event correlation between damages and changes in consumer spending across different weighting schemes. Equal weights have a zero within-event correlation by construction. The sample is the top 50 multi-county disaster events of each type occurring between 2019 and 2025, ranked by total damages. The spending decline for a given county-event pair is computed as the percent change from average daily in-store spending over event days -10 through -3 to the minimum daily in-store spending in the week following the event (days 0 through $+7$), where day 0 is the disaster's reported begin date. The pre-period window is offset to end at day -3 rather than day -1 to avoid including anticipatory spending. r is the Pearson correlation coefficient between a given weighting scheme's county-level damage allocation and the corresponding county-level spending decline, computed separately within each event, and then averaged across the 50 events in the sample. The t-test p-value is from a t-test of the mean of the 50 per-event correlations against a null value of zero (correlation under equal weighting). Results are robust to the nonparametric Wilcoxon signed-rank test. Significance stars on the r column reflect the t-test p-value: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.