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Impact of extreme weather events on healthcare utilization and mortality in the United States

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Climate change is intensifying extreme weather events. Yet a systematic analysis of post-disaster healthcare utilization and outcomes for severe weather and climate disasters, as tracked by the US government, is lacking. Following exposure to 42 US billion-dollar weather disasters (severe storm, flood, flood/severe storm, tropical cyclone and winter storm) between 2011 and 2016, we used a difference-in-differences (DID) approach to quantify changes in the rates of emergency department (ED) visits, nonelective hospitalizations and mortality between fee-for-service Medicare beneficiaries in affected compared to matched control counties in post-disaster weeks 1, 1–2 and 3–6. Overall, disasters were associated with higher rates of ED utilization in affected counties in post-disaster week 1 (DID of 1.22% (95% CI, 0.20% to 2.25%; $P < 0.020$)) through week 2. Nonelective hospitalizations were unchanged. Mortality was higher in affected counties in week 1 (DID of 1.40% (95% CI, 0.08% to 2.74%; $P = 0.037$)) and persisted for 6 weeks. Counties with the greatest loss and damage experienced greater increases in ED and mortality rates compared to all affected counties. Thus, billion-dollar weather disasters are associated with excess ED visits and mortality in Medicare beneficiaries. Tracking these outcomes is important for adaptation that protects patients and communities, health system resilience and policy.

Climate change is driving an increased frequency and intensity of extreme weather events in the United States, such as floods and tropical cyclones[1–3]. The National Oceanographic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI), a US federal agency, tracks billion-dollar weather and climate disasters[4–6]. These are disasters that cause $1 billion US dollars (USD) or more in total loss and damage and account for more than 80% of all weather-related and climate-related damage in the United States[6]. Of the seven categories, five are short-term events (flood, severe storm, tropical cyclone, winter storm and freeze) and two are longer-term events (wildfires and drought). This tracking is a highly visible reference source for decision-making and policy-making for national and subnational governments, such as the White House, and other critical societal stakeholders[7,8].

Since 1980, NOAA NCEI billion-dollar weather disasters have totaled over $2.6 trillion USD in destruction; there were a record-breaking 60 disasters in 2020–2022 alone, and 2023 had an unprecedented 28 confirmed disasters[6]. In addition to the economic

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consequences, climate-sensitive extreme events are already adversely impacting health and healthcare delivery[9–14]. Vulnerable populations, such as those covered by Medicare, are at a higher risk of experiencing the direct and indirect health impacts of extreme weather events than the general population[15–17]. Yet broad, empirical evidence on how these climate-sensitive events impact health outcomes and healthcare utilization is relatively sparse. In addition, NOAA NCEI does not currently include health or healthcare-related considerations into their billion-dollar weather disaster methodology or tracking beyond the immediate death toll. Thus, understanding how such events that cause severe economic devastation are associated with disruptions to healthcare, as well as adverse impacts on human health, are needed.

Studies of short-term weather-related events in the United States have largely focused on one outcome for individual storms[18–24] or multiple storms within the same type of event[25–29]. Analyses of Medicare beneficiaries have mostly focused on cause-specific hospitalizations during the immediate post-disaster period following tropical cyclones[30,31]. There are relatively few studies examining flood, severe storm and winter storm events—and these three categories lack national-level assessments in Medicare beneficiaries. While the mechanisms vary by disaster type (for example, flooding, wind and snow), all weather-related disasters have a common endpoint of infrastructure destruction and/or societal disruption with potentially long-lasting implications[32], providing a means by which they can be compared. These shocks impact patients and the healthcare system in multiple ways that are incompletely understood, potentially extending well beyond the immediate aftermath[21,27,33–35]. As the threats from climate change accelerate, a detailed annual assessment of the impact of NOAA NCEI billion-dollar weather disasters on acute-care utilization and health outcomes has potentially important implications for all-hazard healthcare system resilience, climate change adaptation and health-centered climate policy.

To address this critical evidence gap, we examined claims among all fee-for-service (FFS) Medicare beneficiaries residing in counties that experienced short-term NOAA NCEI billion-dollar weather disasters (flood, severe storm, tropical cyclone and winter storm) to address the following three questions: (1) Are there observable changes in ED visits, nonelective hospitalizations (urgent and emergent) and mortality in the week following the onset of a billion-dollar weather disaster?; (2) Do these changes persist beyond the immediate post-disaster period?; and (3) Are these changes greatest for counties experiencing the highest quartile of reported loss and damage?

Results

Billion-dollar weather disasters and county characteristics

We examined 42 different short-term billion-dollar weather disasters, identified by NOAA NECI, that occurred between 2011 and 2016 (Table 1). These events were categorized into five event types: flood, flood/severe storm, severe storm, tropical cyclone and winter storm. Overall, the disasters affected 69,794,085 nonunique FFS Medicare beneficiaries. Of the 3,143 US counties, 2,039 (65%) were affected by at least one disaster during the study period with disasters largely concentrated in the eastern United States (Fig. 1). Disasters had a mean length of 5 days and potentially affected an average of 14,290 beneficiaries per county and an average of 116 counties (Table 1). Beneficiaries in these counties had a mean age of 71.2 years, 86.5% were white, 45.3% were male and 20.6% were eligible for Medicaid. Many affected counties were in metropolitan areas (48.6%) and the Southern US census region (61.3%; Fig. 1). The unaffected comparison, or control, counties are characterized in Table 1 and show similar characteristics. Characteristics of the wildfire and drought disasters and their affected counties are in Extended Data Table 1 and Extended Data Fig. 1. These counties were excluded as controls because wildfire and droughts are long-term NOAA NCEI billion-dollar weather and climate disasters (Methods), with an average length of a wildfire of 191 days and drought of 298 days (Extended Data Table 1).

Table 1 | Comparison of short-term billion-dollar weather disasters and county characteristics overall for affected and control counties

	Affected	Control	SMD
Number of disasters	42	–	–
Flood	7	–	–
Flood/severe storm	5	–	–
Severe storm	22	–	–
Tropical cyclones	5	–	–
Winter storm	3	–	–
Mean length of disaster (days)	5	–	–
Property and crop loss and damage ($USD, in millions)	343.9	–	–
County characteristics			
Total counties	4,884	18,437	–
FFS Medicare beneficiaries per county[a]	14,290	10,927	0.121
Population of county[b]	133,381	95,822	0.120
Median household income ($USD)[b]	46,052	43,703	0.192
Average age[a]	71.2	71.1	0.040
Age distribution of Medicare beneficiaries [a]			
% <65 years	17.7%	18.1%	0.056
% 65+ years	82.3%	81.9%	
% Male[a]	45.3%	45.7%	0.166
% Non-Hispanic white[a]	86.5%	87.3%	0.054
% Medicaid eligible (dual status)[a]	20.6%	21.4%	0.094
% Persons in poverty[b]	17.8%	18.7%	0.139
% Persons 25+ years with high school diploma[b]	83.9%	83.0%	0.139
Urbanicity[b]			
Metropolitan area	48.6%	45.0%	0.073
Micropolitan area	22.6%	23.3%	0.017
Rural area	13.0%	14.6%	0.047
Small town	15.9%	17.2%	0.035
Census region[b]			
North	6.8%	3.8%	0.135
Midwest	30.6%	28.9%	0.037
South	61.3%	65.7%	0.091
West	1.2%	1.6%	0.028

The control data above represent the control counties selected for the first outcome presented, ED visits. The mean is presented unless otherwise specified. SMD, standardized mean difference. [a]County-level estimates calculated from Master Beneficiary Summary Files (2011–2016). [b]County-level estimates and geographic delineations from the 2015 Area Health Resource File.

Post-disaster week 1: changes in ED visits

Overall, ED visits were 1.09% higher (95% confidence interval (CI), 0.20% to 1.99%) in affected counties 1 week after disaster compared to the reference pre-disaster period (Table 2). Rates of ED visits in nonexposed comparison counties remained essentially unchanged (−0.12% (95% CI, −0.62% to 0.38%)) over the same period, yielding a DID estimate of 1.22% (95% CI, 0.20% to 2.25%; $P < 0.020$). This early rise in ED visits

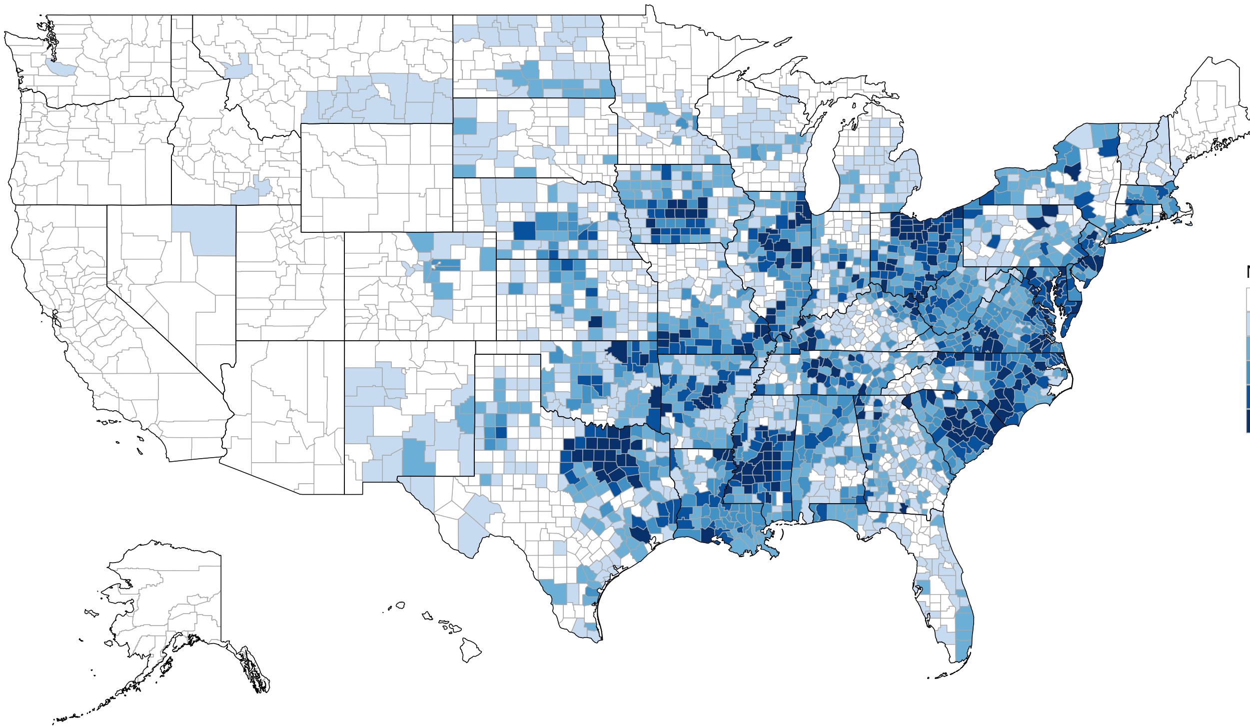

Fig. 1 | Map of US counties affected by short-term NOAA NCEI billion-dollar weather disasters included in the analysis (2011–2016). The blue color gradation of zero events to more than five designates how many of the short-term 42 NOAA NCEI billion-dollar weather and climate disasters included in the study occurred within each county during the study period of 1 January 2011 to 31 December 2016.

was observed across all disaster categories with a DID estimate for tropical cyclones of 3.67% (95% CI, 1.14% to 6.26%) (Table 2).

In absolute terms, given the observed baseline ED rate of 1.89 visits per 1,000 person-days, we would expect an average-sized NOAA NCEI billion-dollar weather disaster (affecting 116 counties that each have an average of 14,290 beneficiaries) to be associated with 268 excess ED visits among FFS Medicare beneficiaries in the subsequent week (Extended Data Table 2). For an average-sized billion-dollar tropical cyclone, we would expect 1,165 excess ED visits in FFS Medicare beneficiaries in post-disaster week 1.

Post-disaster week 1: changes in hospitalizations

In the first week after the onset of a disaster, rates of nonelective hospitalizations remained unchanged overall compared to the reference time period, yielding a DID estimate of 0.75% (95% CI, −0.29% to 1.81%; P = 0.159; Table 2). However, a higher rate of hospitalization was observed in counties exposed to severe storms (DID 1.59% (95% CI, 0.13% to 3.07%); Table 2). In absolute terms, given the observed baseline nonelective hospitalization rate of 0.62 visits per 1,000 person-days, we would expect an average-sized NOAA NCECI billion-dollar severe storm to be associated with 115 excess nonelective hospitalizations in FFS Medicare beneficiaries in post-disaster week 1 (Extended Data Table 2).

Post-disaster week 1: changes in mortality

Overall mortality was 1.15% higher (95% CI, 0.01% to 2.30%) in the affected counties during the first week compared to the reference pre-disaster period (Table 2). Mortality rates in the control counties remained unchanged over the same time period (−0.08% (95% CI, −0.75% to 0.58%)), yielding a DID of 1.40% (95% CI, 0.08% to 2.74%; P = 0.037). When examining individual storm categories, severe storms had an associated differential rise in mortality in affected versus control counties (DID 2.28% (95% CI, 0.35% to 4.26%); Table 2).

Given the observed baseline mortality rate of 0.12 deaths per 1,000 person-days in Medicare beneficiaries, we would expect an average-sized NOAA NCEI billion-dollar weather disaster to be associated with 20 excess deaths in FFS Medicare beneficiaries in the subsequent week. For an average-sized billion-dollar severe storm, we would expect 31 excess deaths in FFS Medicare beneficiaries in post-disaster week 1.

Post-disaster weeks 1–2 and 3–6: changes in ED visits

In the first 2 weeks following disaster onset, rates of ED visits increased by 1.34% (95% CI, 0.58% to 2.10%) in affected versus 0.46% (95% CI, 0.04% to 0.88%) in control counties, resulting in a DID estimate of 0.88% (95% CI, 0.01% to 1.75%; Fig. 2a and Extended Data Table 3). Rates of ED visits were indistinguishable from the pre-period in weeks 3–6 (Fig. 2 and Extended Data Table 4).

Post-disaster weeks 1–2 and 3–6: changes in hospitalizations

When considering all disaster categories together, disasters were not associated with changes in rates of hospitalization 1–2 weeks (Extended Data Fig. 2 and Extended Data Table 3) or 3–6 weeks (Extended Data Fig. 2 and Extended Data Table 4) following a disaster. When considering specific disasters at 3–6 weeks, affected counties for flood disasters had a greater decrease in hospitalizations (−9.19% (95% CI, −11.62% to −6.70%)) compared to control counties (−5.40% (95% CI, −6.74% to −4.03%)) with a DID of −4.01% (95% CI, −6.91% to −1.03%; Extended Data Fig. 2 and Extended Data Table 4).

Post-disaster weeks 1–2 and 3–6: changes in mortality

The increased DID estimate for mortality observed in week 1 persisted. During the first 2 weeks post-disaster there was a DID of 0.79% (95% CI, −0.20% to 1.79%) (Fig. 2b and Extended Data Table 3) and weeks 3–6 a DID of 0.85% (95% CI, 0.05% to 1.67%) (Fig. 2b and Extended Data Table 4). However, within affected counties themselves, the pre–post change in the mortality rate seen during week 1 (1.15% (95% CI, 0.01% to 2.30%)) was attenuated in weeks 1–2 (0.18% (95% CI, −0.68% to 1.04%)) and decreased further in weeks 3–6 (−2.85% (95% CI, −3.52% to −2.16%)).

Table 2 | Comparison of ED visits, nonelective hospitalizations and mortality in Medicare beneficiaries in affected versus control counties for post-disaster week 1 after onset of short-term NOAA NCEI billion-dollar weather disaster

ED visits	Affected counties, baseline rate per 1,000 person-days	Affected counties, relative change (95% CI)	Control counties, baseline rate per 1,000 person-days	Control counties, relative change (95% CI)	DID (95% CI) (affected RR/ control RR)	DID *P* value
Overall	1.89	1.09 (0.20, 1.99)	1.85	−0.12 (−0.62, 0.38)	1.22 (0.20, 2.25)	0.020
Flood	1.83	0.13 (−3.22, 3.59)	1.85	−0.58 (−2.23, 1.09)	0.71 (−3.03, 4.60)	
Flood/severe storm	1.95	0.89 (−2.06, 3.94)	1.88	3.46 (2.01, 4.92)	−2.48 (−5.63, 0.79)	
Severe storm	1.89	1.23 (0.03, 2.44)	1.84	0.04 (−0.66, 0.74)	1.19 (−0.19, 2.60)	
Tropical cyclone	1.92	1.69 (−0.45, 3.87)	1.88	−1.91 (−3.14, −0.66)	3.67 (1.14, 6.26)	
Winter storm	1.82	0.54 (−1.90, 3.03)	1.84	−2.04 (−3.42, −0.64)	2.63 (−0.24, 5.58)	
Nonelective hospitalizations						
Overall	0.62	0.44 (−0.47, 1.37)	0.61	−0.31 (−0.81, 0.20)	0.75 (−0.29, 1.81)	0.159
Flood	0.63	−2.40 (−5.64, 0.94)	0.65	−1.12 (−2.79, 0.59)	−1.30 (−4.96, 2.50)	
Flood/severe storm	0.58	1.32 (−1.61, 4.34)	0.58	1.54 (0.17, 2.93)	−0.22 (−3.39, 3.06)	
Severe storm	0.62	0.16 (−1.09, 1.43)	0.61	−1.41 (−2.11, −0.70)	1.59 (0.13, 3.07)	
Tropical cyclone	0.64	−0.30 (−2.45, 1.89)	0.61	−0.46 (−1.71, 0.80)	0.16 (−2.33, 2.71)	
Winter storm	0.65	3.79 (1.23, 6.43)	0.64	3.09 (1.65, 4.54)	0.68 (−2.16, 3.61)	
Mortality						
Overall	0.12	1.15 (0.01, 2.30)	0.12	−0.08 (−0.75, 0.58)	1.40 (0.08, 2.74)	0.037
Flood	0.12	−1.67 (−6.40, 3.31)	0.12	0.64 (−1.55, 2.88)	−2.29 (−7.43, 3.13)	
Flood/severe storm	0.13	−2.10 (−5.54, 1.47)	0.12	−2.14 (−3.90, −0.35)	−0.39 (−4.31, 3.68)	
Severe storm	0.12	0.81 (−0.77, 2.42)	0.12	−1.41 (−2.38, −0.43)	2.28 (0.35, 4.26)	
Tropical cyclone	0.11	3.00 (0.10, 5.99)	0.11	2.23 (0.47, 4.03)	0.69 (−2.63, 4.12)	
Winter storm	0.13	3.35 (0.47, 6.31)	0.13	4.02 (2.17, 5.90)	−0.65 (−3.91, 2.73)	

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre-disaster versus post-disaster period) and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percentage male, percentage non-Hispanic white, percentage eligible for Medicaid (dual status), percentage in poverty, and percentage of persons over 25 with a high school diploma. The *P* values are two-sided but not adjusted for multiple testing. RR, risk ratio; RUCA, rural-urban commuting area.

Severe storms, similar to week 1, continued to be associated with higher mortality rates in affected counties compared to controls across these extended time periods (weeks 1–2 DID: 1.43% (95% CI, 0.09% to 2.78%); weeks 3–4 DID: 1.93% (95% CI, 0.86% to 3.01%); Fig. 2b and Extended Data Tables 3 and 4).

Warning period

The warning period is defined as the week before the onset of the disaster. This time period had rates for ED visits, nonelective hospitalizations and mortality that were indistinguishable from control counties, overall and across disaster categories (Extended Data Table 5). The one exception was winter storms, for which affected counties had an associated rise in ED visits compared to control counties (DID 3.01% (95% CI, 0.26% to 5.84%)). The top five visit diagnosis categories for winter storms during the warning period were chest pain (4.34%), chronic obstructive pulmonary disease (3.64%), urinary tract infection (3.01%), superficial injury (2.99%) and non-hypertensive congestive heart failure (2.91%; Extended Data Table 6). This was not a substantial change from the week before the warning period (chest pain (4.19%), superficial injury (3.25%), chronic obstructive pulmonary disease (3.19%), urinary tract infection (3.11%) and septicemia (3.06%)).

Stratification of counties by total loss and damage

We stratified counties into quartiles by the total economic value of the loss and damage (that is, property and crop loss) recorded by the county for post-disaster week 1 (Table 3). In counties that experienced the most loss and damage, or quartile 4, ED visits were 2.46% higher (95% CI, 0.63% to 4.33%) in affected counties 1 week after disaster compared to the reference pre-disaster period. Rates of ED visits in nonexposed comparison counties remained relatively unchanged (−0.46% (95% CI, −1.49% to 0.59%)) over the same period, yielding a DID estimate of 2.94% (95% CI, 0.81% to 5.11%). In quartile 3, or the next highest level of economic loss and damage, ED visits were observed to be elevated with a DID estimate of 2.02% (95% CI, 0.01% to 4.08%) and then had no associated changes in quartiles 1 and 2. None of the four quartiles had associated changes in rates of nonelective hospitalizations. For mortality, quartile 4 had elevated mortality with a DID of 2.64% (95% CI, 0.02% to 5.32%), while the mortality rates in quartiles 1–3 were not elevated.

Greatest loss and damage counties versus all affected counties

Outcomes for quartile 4, or the counties with the most loss and damage, for all time periods can be found in Table 4, which also includes the week-1 findings from Table 3. ED visits in week 1, as noted above, had a DID of 2.94% (95% CI, 0.81% to 5.11%). This DID was 2.4 times the increase seen in the analysis of all affected counties (DID 1.22% (95% CI, 0.20% to 2.25%); Table 2). While there were more pronounced findings for ED visits observed in the pre–post-disaster periods in affected counties in weeks 1–2, the DID estimates were unchanged. Observed changes in hospitalizations were unchanged across all time periods, similar to findings for all affected counties (Table 4). However, the DID estimates for mortality in quartile 4 were higher than the findings for all affected counties in all three time periods, specifically 1.9 times higher in week 1, 3.8 times higher in weeks 1–2 and 2.6 times higher in weeks 3–6 (Tables 2 and 4, Fig. 2b and Extended Data Tables 3 and 4). In week 1, the DID for mortality was 2.64% (95% CI, 0.02% to

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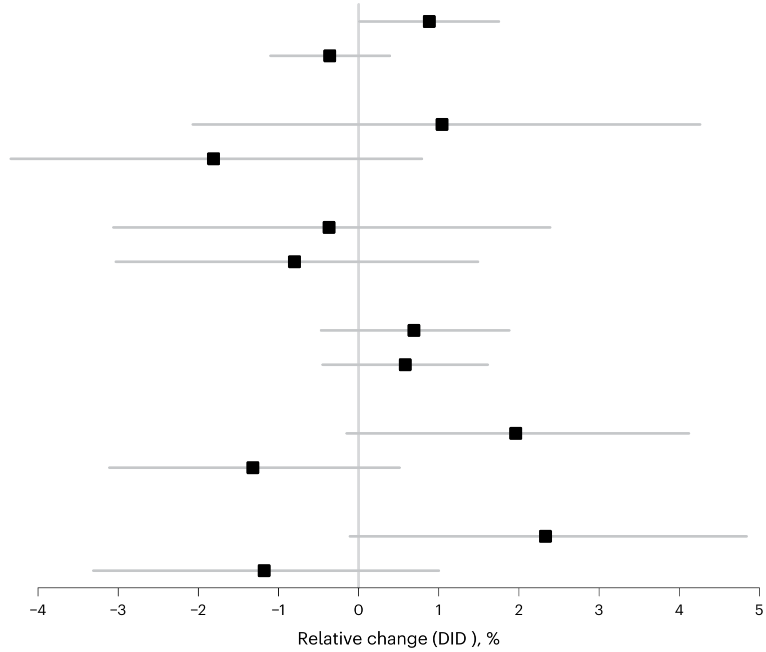
a

ED visits	Affected relative change (95% CI)	DID (95% CI)
Overall		
First 2 weeks	1.34 (0.58, 2.10)	0.88 (0.01, 1.75)
Next 4 weeks	−0.67 (−1.32, −0.02)	−0.36 (−1.10, 0.39)
Floods		
First 2 weeks	0.92 (−1.86, 3.78)	1.04 (−2.07, 4.26)
Next 4 weeks	−3.82 (−6.02, −1.56)	−1.81 (−4.34, 0.79)
Flood/severe storms		
First 2 weeks	3.07 (0.55, 5.66)	−0.37 (−3.06, 2.39)
Next 4 weeks	1.58 (−0.50, 3.70)	−0.80 (−3.03, 1.49)
Severe storms		
First 2 weeks	0.91 (−0.10, 1.94)	0.69 (−0.47, 1.88)
Next 4 weeks	1.10 (0.20, 2.01)	0.58 (−0.45, 1.61)
Tropical cyclones		
First 2 weeks	0.89 (−0.91, 2.73)	1.96 (−0.15, 4.12)
Next 4 weeks	−3.02 (−4.55, −1.46)	−1.32 (−3.11, 0.51)
Winter storms		
First 2 weeks	2.78 (0.64, 4.97)	2.33 (−0.11, 4.84)
Next 4 weeks	−5.09 (−6.89, −3.25)	−1.18 (−3.31, 1.00)



b

Mortality	Affected relative change (95% CI)	DID (95% CI)
Overall		
First 2 weeks	0.18 (−0.68, 1.04)	0.79 (−0.20, 1.79)
Next 4 weeks	−2.85 (−3.52, −2.16)	0.85 (0.05, 1.67)
Floods		
First 2 weeks	−1.11 (−4.51, 2.42)	1.24 (−2.57, 5.20)
Next 4 weeks	−6.80 (−9.29, −4.25)	−0.78 (−3.71, 2.23)
Flood/severe storms		
First 2 weeks	−1.16 (−3.89, 1.65)	0.56 (−2.54, 3.76)
Next 4 weeks	1.85 (−4.15, 0.51)	−0.15 (−2.73, 2.51)
Severe storms		
First 2 weeks	−0.60 (−1.72, 0.54)	1.43 (0.09, 2.78)
Next 4 weeks	−4.79 (−5.65, −3.92)	1.93 (0.86, 3.01)
Tropical cyclones		
First 2 weeks	0.93 (−1.09, 2.99)	−1.26 (−3.56, 1.11)
Next 4 weeks	3.40 (1.77, 5.05)	0.17 (−1.67, 2.04)
Winter storms		
First 2 weeks	2.14 (−0.20, 4.53)	−1.00 (−3.64, 1.72)
Next 4 weeks	−1.32 (−3.29, 0.70)	−0.62 (−2.92, 1.74)

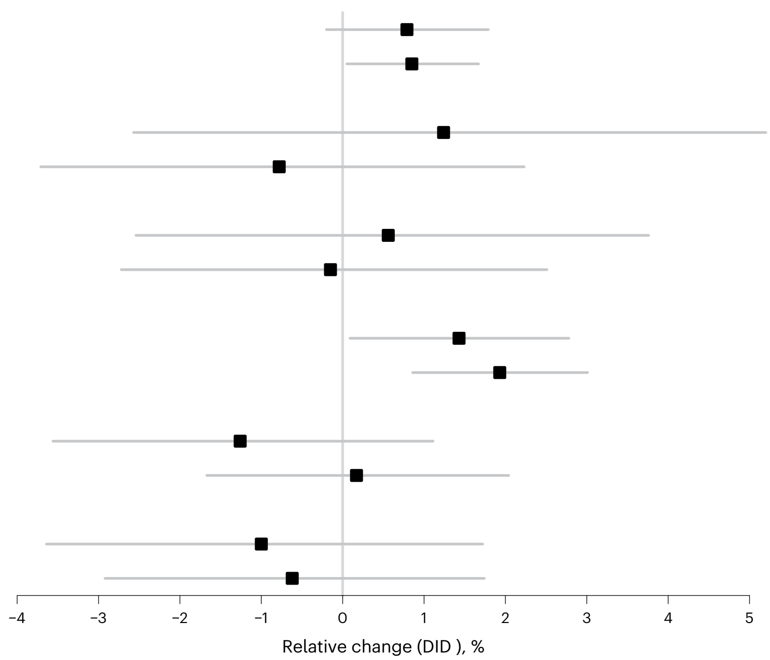


Fig. 2 | Forest plots of ED visit and mortality relative change and DID for affected counties in post-disaster weeks 1–2 and weeks 3–6 in Medicare beneficiaries exposed to a short-term NOAA NCEI billion-dollar weather disaster in the United States. a, A forest plot of ED visit relative change and DID with 95% CI in 271,253,459 nonunique US FFS Medicare beneficiaries in 4,884 affected counties and 18,437 control counties for weeks 1–2 and 3–6 for 42 aggregated overall and each NOAA NCEI billion-dollar disaster category (floods, floods/severe storms, severe storms, tropical cyclones and winter storms). **b**, A similar forest plot, based on the same sample sizes, for mortality. 95% CI (mean ± 1.96 × s.e.m.).

5.32%) for the top-quartile counties versus all affected counties (DID 1.40% (95% CI, 0.08% to 2.74%)). In weeks 1–2, the DID for mortality was 3.03% (95% CI, 1.03% to 5.08%) for the top-quartile counties versus all affected counties (DID 0.79% (95% CI, −0.20% to 1.79%)). For weeks 3–6, the top-quartile counties had a DID of 2.23% (95% CI, 0.57% to 3.92%) versus all affected counties (DID 0.85% (95% CI, 0.05% to 1.67%)).

Table 3 | Stratified analyses by quartiles of county loss and damage for ED visits, nonelective hospitalizations and mortality in Medicare beneficiaries for post-disaster week 1

Quartile 4 (most damage)	Affected counties, baseline rate per 1,000 person-days	Affected counties, relative change (95% CI)	Control counties, baseline rate per 1,000 person-days	Control counties, relative change (95% CI)	Diff-in-diff (95% CI) (affected RR/ control RR)
ED visits	1.90	2.46 (0.63, 4.33)	1.85	−0.46 (−1.49, 0.59)	2.94 (0.81, 5.11)
Nonelective hospitalizations	0.63	1.43 (−0.48, 3.37)	0.62	−0.37 (−1.42, 0.69)	1.80 (−0.38, 4.04)
Mortality	0.12	3.04 (0.80, 5.34)	0.12	0.43 (−0.92, 1.79)	2.64 (0.02, 5.32)
Quartile 3					
ED visits	1.87	2.03 (0.28, 3.81)	1.84	0.01 (−0.98, 1.01)	2.02 (0.01, 4.08)
Nonelective hospitalizations	0.63	−0.04 (−1.80, 1.75)	0.62	−0.25 (−1.24, 0.74)	0.21 (−1.80, 2.27)
Mortality	0.12	−0.14 (−2.31, 2.07)	0.12	−0.47 (−1.78, 0.86)	1.80 (−0.76, 4.42)
Quartile 2					
ED visits	1.91	−1.00 (−2.71, 0.75)	1.87	−0.07 (−1.06, 0.92)	−0.92 (−2.89, 1.08)
Nonelective hospitalizations	0.62	0.20 (−1.57, 2.01)	0.61	−0.36 (−1.34, 0.63)	0.56 (−1.47, 2.64)
Mortality	0.12	0.72 (−1.55, 3.04)	0.12	0.25 (−1.13, 1.65)	−0.77 (−3.48, 2.01)
Quartile 1 (least damage)					
ED visits	1.88	1.20 (−0.62, 3.05)	1.86	−0.15 (−1.13, 0.84)	1.35 (−0.71, 3.47)
Nonelective hospitalizations	0.62	0.16 (−1.70, 2.05)	0.60	−0.30 (−1.30, 0.72)	0.46 (−1.65, 2.62)
Mortality	0.12	1.85 (−0.58, 4.35)	0.12	−0.11 (−1.45, 1.25)	1.21 (−1.56, 4.05)

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre-disaster versus post-disaster periods) and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percentage male, percentage non-Hispanic white, percentage eligible for Medicaid (dual status), percentage in poverty and percentage of persons over 25 years with a high school diploma.

Table 4 | ED visits, nonelective hospitalizations and mortality in Medicare beneficiaries for the counties that experienced the top quartile of loss and damage (quartile 4) for aggregated overall for post-disaster week 1, weeks 1–2 and weeks 3–6

Analyses restricted to quartile 4 counties (most damage) overall, post-disaster week 1	Affected counties, baseline rate per 1,000 person-days	Affected counties, relative change (95% CI)	Control counties, baseline rate per 1,000 person-days	Control counties, relative change (95% CI)	DID (95% CI) (affected RR/ control RR)
ED visits	1.90	2.46 (0.63, 4.33)	1.85	−0.46 (−1.49, 0.59)	2.94 (0.81, 5.11)
Non-elective hospitalizations	0.63	1.43 (−0.48, 3.37)	0.62	−0.37 (−1.42, 0.69)	1.80 (−0.38, 4.04)
Mortality	0.12	3.04 (0.80, 5.34)	0.12	0.43 (−0.92, 1.79)	2.64 (0.02, 5.32)
Analyses restricted to quartile 4 counties (most damage) overall, post-disaster weeks 1–2					
ED visits	1.91	1.75 (0.19, 3.34)	1.84	0.45 (−0.42, 1.34)	1.29 (−0.49, 3.11)
Non-elective hospitalizations	0.64	0.86 (−0.88, 2.62)	0.63	−0.49 (−1.43, 0.47)	1.35 (−0.64, 3.38)
Mortality	0.12	2.56 (0.84, 4.31)	0.12	−0.46 (−1.46, 0.55)	3.03 (1.03, 5.08)
Analyses restricted to quartile 4 counties (most damage) overall, post-disaster weeks 3–6					
ED visits	1.90	−1.11 (−2.46, 0.27)	1.85	−0.80 (−1.56, −0.04)	−0.31 (−1.87, 1.28)
Non-elective hospitalizations	0.64	−1.75 (−3.36, −0.10)	0.63	−2.10 (−2.97, −1.21)	−0.36 (−1.52, 2.27)
Mortality	0.12	−0.74 (−2.14, 0.68)	0.12	−2.90 (−3.70, −2.10)	2.23 (0.57, 3.92)

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre-disaster versus post-disaster period) and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percentage male, percentage non-Hispanic white, percentage eligible for Medicaid (dual status), percentage in poverty and percentage of persons over 25 years with a high school diploma.

Lastly, there were no differences observed in the overall warning periods of top-quartile counties (Extended Data Table 7).

Sensitivity analysis

After limiting affected and control counties to those that could be matched within NOAA climate regions, our post-disaster week-1 analyses (Extended Data Table 8) revealed similar findings (Table 2). Overall, ED visits had an associated DID estimate of 1.42% (95% CI, 0.40% to 2.45%), nonelective hospitalizations had a DID of 0.85% (95% CI, −0.17% to 1.88%) and mortality has a DID of 1.31% (95% CI, −0.05% to 2.69%; Extended Data Table 8).

Discussion

In this analysis of FFS Medicare beneficiaries residing in counties exposed to 42 different short-term NOAA NCEI billion-dollar weather disasters during 2011–2016, we observed meaningful increases in the rates of ED visits and mortality in the post-disaster period. There was an associated increase in ED utilization through post-disaster week 2 and beneficiary mortality through post-disaster week 6, the end of our study period. Rates of nonelective hospitalizations were unchanged. These findings were observed to be more pronounced in the counties with the greatest total economic value of loss and damage with mortality rate increases approximately two to four times higher than all affected counties. While our findings were similar within each disaster category, as expected, there was some variation in outcome trends over time. Severe storms was the only event category with increased hospitalizations in post-disaster week 1 and was associated with the highest mortality rates throughout the 6-week study period. Taken together, these findings suggest that NOAA NCEI billion-dollar weather disasters have broad and lasting impacts on healthcare utilization and outcomes among beneficiaries.

These findings underscore how examining a range of outcomes in both the immediate and longer-term post-disaster periods may provide a more comprehensive picture of the harms associated with climate-sensitive weather disasters. Furthermore, total damage allows comparison across a range of disasters, while also capturing the associated health and healthcare shocks that infrastructure destruction and societal disruption can bring (for example, power outages, loss of communication, transportation challenges, displacement and facility closures). Furthering this possible conceptual model, our stratified analysis by total loss and damage suggests a potential exposure–response relationship between the magnitude of disaster-related destruction and mortality. While more work needs to be done, county-level loss and damage may serve as an indicator of resultant mortality among older persons and those with certain disabilities covered by Medicare—which are especially vulnerable populations.

This work has four other potential applications. First, the United States has experienced record-breaking numbers of billion-dollar weather disasters since the end of our study period in 2016. This makes it increasingly important to understand, in as real time as possible, how more frequent and intensified extreme weather events impact healthcare utilization and outcomes. One approach is to systematically and comprehensively track this data in regularly updated metrics or indicators. Integrating this type of analysis within the existing framework of the US federal government's NOAA NCEI billion-dollar weather and climate disaster tracking system could present an opportunity not only to better understand health-related outcomes for extreme weather events, but also to expand the tracking's application and impact. For example, this could help drive health-related decision-making and policy at the federal and subnational levels, including making healthcare systems more resilient to climate change using an all-hazards approach and developing climate policy that centers health and healthcare considerations. Second, NOAA NCEI currently only reports the number of immediate deaths associated with each billion-dollar weather disaster. Our methodology provides proof of concept for how mortality reporting could be expanded to include longer-term data. Third, this study could lay the groundwork for subsequent work that determines the cost of increased healthcare utilization by Medicare beneficiaries associated with billion-dollar disasters, which are costs borne by US taxpayers. These costs could be tracked for NOAA NCEI billion-dollar disasters and potentially included in the total costs associated with each event. Fourth, and finally, this work also helps to better understand the implications for healthcare delivery following climate-sensitive extreme weather events, which is much less well understood.

Globally, there are various mechanisms that track total loss and damage from extreme weather in USD across the globe. Munich Re and Swiss Re, for example, are global reinsurers that release annual assessments of the economic losses from global extreme weather events. Thus, these annual assessments designate events that caused at least one billion dollars or more in economic damage, which could permit extrapolation of our study findings to other countries. However, these global billion-dollar events often occur in high-income countries given the degree of infrastructure that must be impacted to reach that threshold. Increased resiliency in high-income countries is likely to be protective to some degree. This is supported by our more modest mortality results compared to a prior global examination of the mortality burden following tropical cyclones[36]. That study found that in the 2 weeks after exposure to a tropical cyclone, global mortality was increased by 6% overall, although there was substantial variation across regions with East and South Asia experiencing the highest deaths. While our threshold and findings do not directly translate to low-income and middle-income countries, our study could provide a conceptual model for a tracking of healthcare utilization and outcomes for practice and policy purposes using a more relevant country-level monetary threshold.

This study is in line with previous literature examining the adverse acute-care utilization and health outcomes of tropical cyclones, severe storms, floods and winter storms in the United States[21,26,27]. Previous work has largely focused on tropical cyclones, and our finding of an early rise in ED visits is consistent[18,29]. Studies have revealed excess mortality after tropical cyclones at 3 months[19,33] or beyond[34], especially in more vulnerable populations[37–39]. While the lack of a change in hospitalizations overall and by most event categories in the post-disaster period may seem unexpected, earlier studies suggest that there could be a complex interplay unfolding. Following large-scale and destructive disasters, healthcare utilization is likely impacted by multifactorial drivers such as the degree of post-disaster pathology and acuity, care avoidance, transportation disruption, facility closure and changes in provider admission thresholds. Our analysis captured hospitalizations independent of location, and thus this finding was not driven by beneficiary displacement. Evidence on hospitalizations following tropical cyclones has shown that certain categories of admission diagnoses decline, while others are elevated in the immediate post-disaster period[30,31]. This could explain that when aggregated overall, there are no changes in hospitalizations.

There was also a marked decline in nonelective hospitalizations at 3–6 weeks after exposure to billion-dollar flood disasters. Previous studies observed a decrease in ED visits in the immediate post-disaster period following flood events[22] and examined the associations between inpatient elective care and the strength of tropical cyclones based on wind speeds[40]. There was a suggestion of a nearly linear relationship between wind speed and the initial drop in elective services, with the strongest events having a much more notable initial decline in the first through third post-event months. The strongest events were also associated with longer-lasting declines, at times extending beyond the end of the study period of 1 year. Thus, there could be cause-specific rises for certain nonelective hospitalizations that are being offset by declines due to factors like care avoidance or an inability to reach facilities. Future work is needed to better understand these likely multifactorial relationships.

Severe storms were uniquely observed to have an increase in nonelective hospitalizations and were associated with the highest mortality rates throughout the 6-week study period. Previous literature examined the observed phenomenon of 'thunderstorm asthma', which is a sequence of weather-related events that can exacerbate respiratory disease. This provides one mechanism possibly driving higher week-1 hospitalizations—and possibly even mortality—following severe storms[41,42]. For floods and winter storms, studies that have examined utilization patterns for specific diseases provide additional insight on mechanisms possibly driving our summative results[22,43–45]. For example, hospital admissions for cardiovascular disease decrease during a winter storm's heavy snowfall, but then increase 2 days after[43].

Our study has limitations. The observational nature of this study precludes concluding a causal relationship between weather disasters and the studied outcomes. In particular, we could not exclude spillover to control counties, as they were matched based on geography and urban–rural status with adjacent counties excluded. We also could not exclude the possibility of extreme weather events not reaching the designation of a NOAA NCEI billion-dollar disaster affecting our ability to accurately estimate temporal trends in comparison counties. However, billion-dollar disasters are estimated to account for more than 80% of total extreme weather damage in the United States[6]. While our hypothesis is that total loss and damage associated with an extreme weather disaster is a proxy for the magnitude and severity of an event, economic damage could exceed a billion dollars when a small-sized or average-sized event strikes more densely populated and/or higher-income counties. Given that wealthier counties may be more resilient to extreme weather events, our analysis of only billion-dollar disasters may underestimate healthcare utilization and mortality. Our affected counties, though, had a mean of about 18% persons in poverty, which is above the national average of 13.4%[46]. Additionally, our results may not be generalizable beyond the Medicare population and the predominantly non-Hispanic white sample living in the South and Midwest. Lastly, given our analysis only includes events that met the NOAA NCEI billion-dollar threshold, it excludes those with less documented loss and damage (that is, smaller, more frequent extreme weather events). Thus, these results are not a comprehensive analysis of all extreme weather events during this time period.

In conclusion, exposure to NOAA NCEI billion-dollar weather disasters was associated with increased ED utilization and a rise in mortality in Medicare beneficiaries, which was more pronounced in counties with the greatest degree of damage. As climate-sensitive weather events intensify, identifying ways to minimize disruptions in healthcare delivery following these disasters may be an important target to reduce the adverse health impacts.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41591-024-02833-x.

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Methods

Study approval was obtained by the Office of Human Research Administration at the Harvard T.H. Chan School of Public Health. Informed consent was not obtained, as the data were previously collected, de-identified administrative data. This observational study sought to evaluate if exposure to billion-dollar weather and climate disasters was associated with changes in acute-care utilization and mortality in FFS Medicare beneficiaries. We used databases from the US federal NOAA NCEI and the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to identify affected counties. We then evaluated exposure to these disasters using a DID approach comparing changes in affected counties to those in matched control counties during the same time periods to control for temporal fluctuations even in the short term (for example, due to holidays, seasonal infectious disease patterns).

Billion-dollar weather disasters and affected counties

In the United States, the federal NOAA NCEI has tracked billion-dollar weather and climate disasters since 1980 (refs. 4–6). These events are defined as billion-dollar disasters because they have caused at least one billion dollars in economic losses, as measured through the data sources included in the NOAA NCEI analyses. NOAA NCEI notes that while '$1 billion USD is an arbitrary threshold, these specific events account for the majority (>80%) of the damage from all recorded US weather and climate events. In fact, these billion-dollar disaster events are becoming an increasingly larger percentage from the full distribution of weather-related events at all scales and loss levels[4]. This event tracking is highly cited in decision-making, policy and communication forums in the United States. This approach also allows for a standardized comparison across different types of climate-sensitive events.

There were 69 billion-dollar weather and climate disasters between 1 January 2011 and 31 December 2016 (Supplementary Table 1)[6]. While the overall summary characteristics for each of these events are publicly available through NOAA NCEI, county-level data are not. Thus, to identify the specific counties that were affected by these disasters, we identified these same events in SHELDUS (version 16.1)[47]. This database is managed by Arizona State University Center for Emergency Management and Homeland Security and is available for purchase. It contains county-level direct losses in the form of property and crop loss for the United States, and we identified the NOAA NCEI billion-dollar weather and climate disasters in the SHELDUS database.

A county, as designated by a unique Federal Information Processing Standards code, was deemed affected by a billion-dollar disaster if there was any amount of property damage and/or crop loss (>$0 USD) or an injury or fatality in that county in the SHELDUS dataset attributable to that event during the dates of the billion-dollar disaster. SHELDUS data include both direct property losses and crop insurance claims at the county level. Not all disasters listed as a billion-dollar disaster in NOAA NCEI were available in the SHELDUS database at the time of the initial analysis. Given the differing data sources, not all disasters totaled a billion dollars in damages based on SHELDUS data, but they were still used based on the identification as a billion-dollar disaster through the NOAA NCEI methodology. While NOAA NCEI outlines billion-dollar disasters as either a flood or a severe storm, SHELDUS has a combined category of flooding/severe storm, thus creating the additional category.

A total of 51 of these billion-dollar disasters were identified in SHELDUS spanning the following categories: floods, severe storms, floods/severe storms, tropical cyclones, winter storms, wildfires and droughts (Supplementary Table 1). However, we wished to create an aggregated overall analysis that included short-term events with localized impacts given our exposure variable was county-level direct property damage and crop loss insurance claims. The wildfire and drought disasters were lengthy, long-term events (average duration of 191 and 298 days, respectively; Extended Data Table 1), caused impacts to health well outside the county of origin (for example, wildfire smoke plumes traveling far distances), and were hypothesized to have uniquely different mechanisms through which health harms occurred independent of county-level damage (for example, dust storms) than the remaining billion-dollar events. Thus, the eight wildfire and drought disasters that were identified were removed from the analyses, although they were still considered in our methodology to ensure an optimal selection of control counties. Counties that were experiencing a billion-dollar wildfire or drought disaster were excluded from being selected as a control county. In two instances, disasters that were listed separately by NOAA NCEI were combined because of overlapping dates and counties in the SHELDUS database.

Our final analysis included 5,054 nonunique affected counties and 42 events in five categories (flood, severe storm, flood/severe storm, tropical cyclone and winter storm disasters) that occurred between 2011 and 2016. Only 156 affected counties (3.1%) had $0 of property or crop loss and were identified solely on an injury or fatality. Supplementary Table 1 lists the name, type of disaster, start and end dates, and the number of affected counties. For those disasters with varying end dates when comparing NOAA NCEI and county-level data in SHELDUS, the latest end date was used to ensure that a given disaster has the same start and end date across all counties affected by the disaster.

Affected and control Medicare beneficiaries

Medicare is a US federal health insurance program for individuals who are 65 years of age or older or have certain disabilities and covers nearly all eligible individuals for a total of over 65 million beneficiaries[48]. This study included all FFS Medicare beneficiaries, including those under the age 65, residing in affected or control counties from 2010 to 2016.

Medicare beneficiaries were considered residents of an affected county if, during the disaster, the affected county was their place of residence as indicated in the most recently reported annual Medicare Master Beneficiary Summary File (MBSF). The same procedure occurred for Medicare beneficiaries residing in control counties. County of residence, death date and demographic characteristics were obtained from the MBSF. Their enrollment status was determined at the start of the year, so they were fully enrolled for a year unless they died. A transition from FFS Medicare to Medicare Advantage is restricted to the start of the year, except in exceptional situations.

ED visits, nonelective hospitalizations and mortality (outcomes)

We examined rates of total ED visits, nonelective hospitalizations and mortality. These outcomes were identified from Medicare inpatient and outpatient claims and the MBSF, aggregated at the county level. To account for potential displacement, ED visits and hospitalizations were attributed to the beneficiary's county of residence for that year, regardless of where the visit occurred.

ED visits were identified from a 5% random sample in 2010 and a 20% random sample in 2011–2016 from Medicare inpatient and outpatient claims. Hospitalizations were identified using 100% inpatient claims. Mortality was calculated based on the death date from the MBSF and was available for 100% of the FFS population. Hospitalizations were defined as either urgent or emergent visits only (nonelective).

Pre-periods and post-periods

We designated day 0 as the start of each disaster. We examined utilization rates in three time periods following the start of a disaster: week 1 (days 0–6), weeks 1–2 (days 0–13) and weeks 3–6 (days 14–41). We selected these time periods based on our a priori hypothesis that there would be associated changes in acute-care utilization and mortality beyond the immediate post-disaster period, interpretation of previous literature and unpublished work (authors same as this paper). The corresponding pre-periods were equivalent lengths of time leading up to the disaster, with a 1-week gap immediately before the disaster excluded from the pre-period to avoid altered utilization that may occur with a disaster warning. This 1-week gap before the disaster is termed the warning period (days −1 to −7). In summary, we defined the pre-period (comparison pre-period) and post-period (from event start day 0) by the following:

- Warning period
  - Post-period: days −1 to −7 (1 week)
  - Comparison pre-period: days −8 to −21

- Period 1
  - Post-period: days 0–7 (1 week)
  - Comparison pre-period: days −8 to −14

- Period 2
  - Post-period: days 0–13 (2 weeks)
  - Comparison pre-period: days −8 to −21

- Period 3
  - Post-period: days 14–41 (4 weeks)
  - Comparison pre-period: days −22 to −49

Thus, the comparison pre-period contains a 7-week pre-disaster period given the 1-week gap for the warning period. The post-period (from event start day 0) contains a 6-week post-disaster period. For counties that were affected by more than one disaster at a time, days were counted relative to the first disaster until the start of the second disaster. Once the second disaster started, the days were counted only relative to the second disaster. If a county had a conflicting disaster for the full pre-period or post-period, the county was not included in the analysis for either that time period or disaster. Note that for this analysis, we did not take into account the end date of the disaster and instead standardized all disasters to begin on day 0 independent of the end date.

County characteristics

The following characteristics were captured at the county-level: FFS Medicare beneficiaries per county, population of county, median household income, average age, age distribution of beneficiaries, percentage male, percentage non-Hispanic white, percentage eligible for Medicaid (dual status), percentage in poverty, percentage of persons over 25 years with a high school diploma, RUCA and census region. County characteristics were obtained from two data sources: the 2015 Area Health Resource File[49] and the MBSF. The Area Health Resource File characteristics included the average population of the county, median household income, percentage living in poverty, percentage of persons over 25 years with a high school diploma, RUCA and census region. We also identified the following characteristics of Medicare beneficiaries in each county from the MBSF and aggregated them at the county-level: percentage male, percentage white, average age and percentage eligible for Medicaid (dual status).

Matching and selection of control counties

In our primary analysis, we matched each affected county with up to five control counties within the same census region and RUCA designation. We used ten different levels of RUCA, thus considering varying levels of urbanicity.

Counties directly adjacent to affected counties or those experiencing a different disaster at the same time or in the preceding 6 months were not eligible to be selected as controls. We selected a 6-month period based on previous literature and our own unpublished analyses (authors same as this paper), which showed reassuring trends that elevated outcomes did not persist beyond 6 months after a billion-dollar weather and climate disaster. Therefore, even if a control county had suffered a billion-dollar weather disaster 7 months ago, we felt it was unlikely that rates of ED visits, nonelective hospitalizations and mortality would be elevated because of the previous disaster. Given the geographic diversity and annual frequency of these events (Extended Data Fig. 2), we attempted to find a time period that was conservative, yet also allowed us to minimize the number of events and counties for which we couldn't find matched controls.

To avoid dropping affected counties due to matching, the other county characteristics were adjusted for in regression models. Only 170 counties were unmatched (3.4%; Supplementary Table 2).

For our sensitivity analyses, we matched based on US climate regions, as defined by NOAA[50]. These are nine regions that have been identified to be climatically consistent. They include Northeast, Upper Midwest, Ohio Valley, Southeast, Northern Rockies and Plains, South, Southwest and Northwest. These regions are defined based on state borders. There were 318 counties unmatched (6.3%).

Statistical analyses

Association between billion-dollar disasters and ED visits, hospitalizations and mortality. We specified a county-level negative binomial model with the weekly number of total ED visits as the outcome. Since counties have different population sizes, the number of beneficiary-days was included as an offset (on the log scale). We calculated beneficiary-days using the following methodology. We added up the total number of FFS Medicare beneficiaries living in all the counties affected by a given disaster in a given year and multiplied that number by the number of days in the analysis window (for example, by 7 when examining the number of ED visits during the first week following the disaster). This product was used as the beneficiary-days offset. The same was done for control counties. While alternative Medicare Advantage insurance plans are available, changes from FFS Medicare to Medicare Advantage are almost exclusively limited by law to the 1st of January and would not affect the accuracy of our count.

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre-disaster versus post-disaster period), and the interaction between the two. The interaction term from this DID model captures, on a relative scale, the extent to which outcomes in affected counties changed more (or less) than the temporal change in control counties. All models included the disaster-specific match group as a fixed effect so that comparisons were made within each affected county's set of matches. We also adjusted for the following county characteristics: population of county, median household income, average age, percentage male, percentage non-Hispanic white, percentage eligible for Medicaid (dual status), percentage in poverty and percentage of persons over 25 years with a high school diploma.

From this DID model, we estimated the relative change between the pre-period and post-period rates for both affected and control counties, with control counties capturing temporal fluctuations. This same primary DID model then compared relative changes in affected counties to relative changes in control counties. We repeated these analyses for the additional time periods, including the warning period (days −1 to −7). Analyses were done separately for each disaster category, as well as overall. Analogous models were run for total nonelective hospitalizations and total mortality.

Unadjusted P values are shown for the primary results for ED visits, hospitalizations and mortality in week 1, with CIs for all other results. Of note, there is a risk of possible false positives with three unadjusted P values, as provided in the paper. Analyses were conducted using SAS version 9.4 (SAS Institute).

Winter storm warning period ED visit types

To understand the different types of ED visits that were driving the changes in ED visit rates during the winter storm warning period, we repeated the ED visit models to determine the most common Clinical Classifications Software categories for both the warning period (days −7 to −1) and the week before or warning pre-period (days −14 to −8). The frequency and percentage were identified.

General event-specific excess ED visits and mortality
For each type of disaster, we calculated the average number of FFS Medicare beneficiaries within an affected county and the average number of affected counties. We then multiplied the baseline event rate by 7 days and the average number of beneficiaries and average number of affected counties and by the DID estimate of the increased number of events to get an estimate for the additional number of people affected by the storm for each outcome.

Stratification by quartiles of total loss and damage
To examine if our results varied by the severity of loss and damage, we repeated our models stratifying counties by quartiles of total loss and damage (Tables 3 and 4). Given that the county-level economic damage for the NOAA NCEI billion-dollar weather disasters was obtained from the SHELDUS database, our economic damage totals use these total property and crop loss values. All counties, independent of event type, were stratified into quartiles based on this county-level data.

Counties in the highest quartile of damage (quartile 4) experienced a mean damage of \$57,938,978 with a range of \$622,657–\$12,506,403,336 in property and crop loss according to the SHELDUS database. Counties in quartile 3 experienced a mean cost of \$229,881 with a range of \$54,320–\$619,356 in property and crop loss, while counties in quartile 2 experienced a mean of \$24,823 and a range of \$10,310–\$54,320. Counties in the lowest quartile of damage (quartile 1), which were the counties that were least impacted, experienced a mean damage of \$3,220 with a maximum of \$10,310.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
Healthcare utilization and outcome data for all analyses were based on administrative data for FFS Medicare beneficiaries. These data cannot be shared by the authors due to regulations, but they can be acquired or purchased from Centers for Medicare and Medicaid Services. The NOAA NCEI data on billion-dollar weather and climate disasters are publicly available. SHELDUS cannot be shared by authors due to regulations, but it can be acquired or purchased from Arizona State University.

Code availability
The code is available at GitHub and can be found at https://github.com/Billion-Dollar-Weather-Medicare/ED-Hospitalizations-Mortality/.

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Author contributions
R.N.S., L.G.B., J.P., G.A.W., E.J.O. and A.K.J. designed the study. J.P. and E.J.O. analyzed data. R.N.S., L.G.B., J.P., G.A.W., E.J.O. and A.K.J. interpreted data. R.N.S., L.G.B., J.P., G.A.W., E.J.O. and A.K.J. wrote the paper. All authors reviewed, edited and approved the final paper.

Competing interests
R.N.S. reports no relevant disclosures or grants. L.G.B. reports receiving grant funding from the Association of American Medical Colleges, the National Institutes of Health National Institute on Aging (R56AG075017), and the Agency for Healthcare Research and Quality (R01HS029781), as well as consulting fees from the Emergency Medicine Policy Institute. G.A.W. reports receiving consulting income from the Health Effects Institute and Google. J.P. and E.J.O. report no relevant disclosures or grants. A.K.J. was on leave from Brown University while serving as the White House COVID-19 Response Coordinator. However, this research and work was completed while A.K.J. was employed at the Harvard T.H. Chan School of Public Health and Brown University School of Public Health, and the findings and views in this paper do not reflect the official views or policy of the White House during the tenure of A.K.J. there. A.K.J. otherwise reports no relevant disclosures or grants.

Additional information
Extended data is available for this paper at https://doi.org/10.1038/s41591-024-02833-x.

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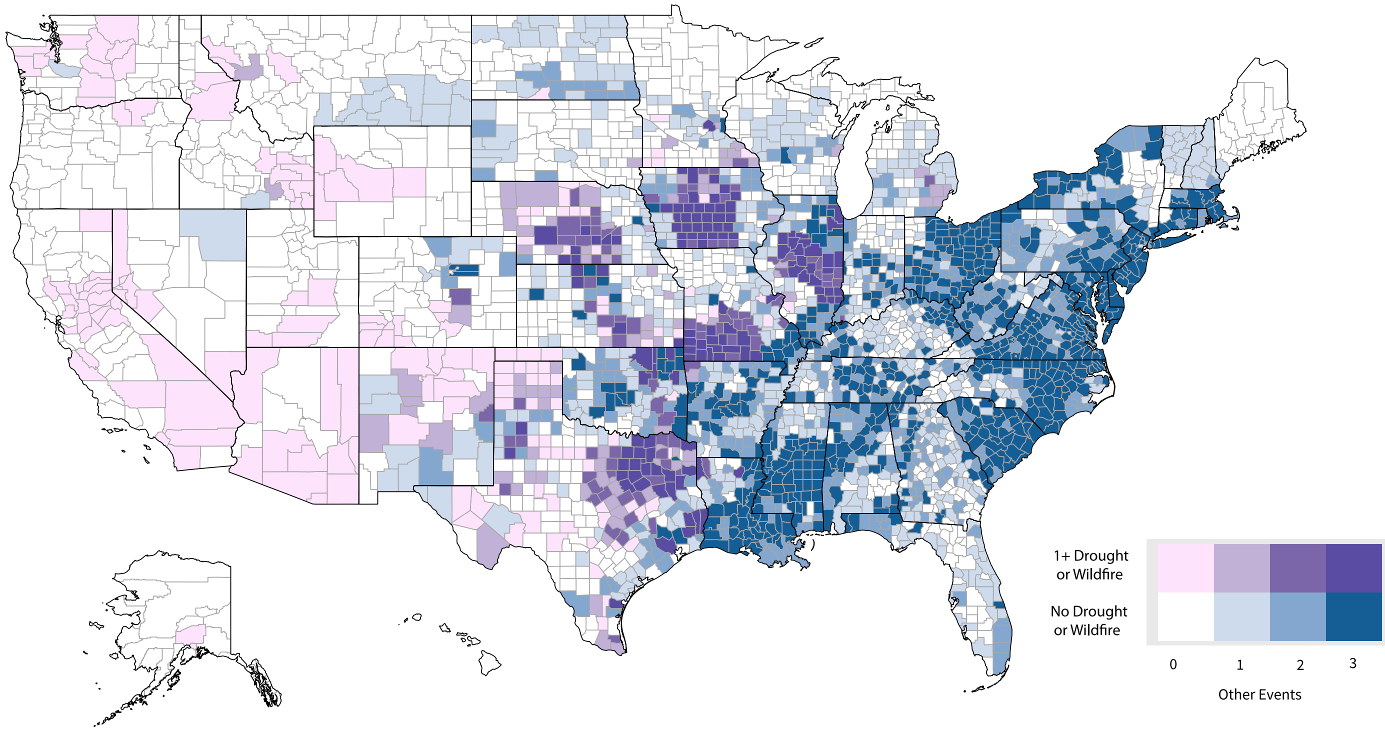

Extended Data Fig. 1 | Map of NOAA NCEI billion-dollar weather and climate disasters included in the analysis (2011–2016) which includes wildfires and droughts that were considered in our selection of controls. The color of the county designates the number of long-term drought or wildfires events and the number of short-term events that included flood, flood/severe storm, severe storm, tropical cyclone, and winter storms during the study period of January 1, 2011 – December 31, 2016. U.S., United States; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information.

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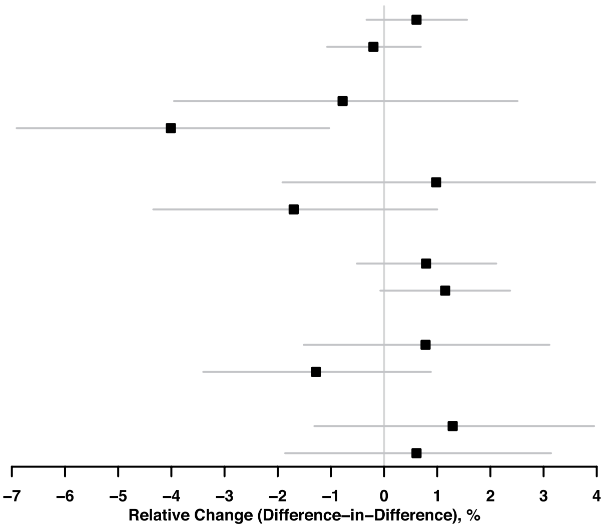
Non-elective Hospitalizations	Affected Relative Change (95% CI)	Diff–in–Diff (95% CI)
Overall		
First Two Weeks	0.26 (−0.56, 1.09)	0.61 (−0.33, 1.56)
Next Four Weeks	−2.71 (−3.46, −1.95)	−0.20 (−1.07, 0.69)
Floods		
First Two Weeks	−2.02 (−4.81, 0.85)	−0.78 (−3.95, 2.51)
Next Four Weeks	−9.19 (−11.62, −6.70)	−4.01 (−6.91, −1.03)
Flood/Severe Storms		
First Two Weeks	3.16 (0.46, 5.92)	0.98 (−1.91, 3.97)
Next Four Weeks	−0.63 (−3.06, 1.85)	−1.70 (−4.34, 1.00)
Severe Storms		
First Two Weeks	−1.01 (−2.13, 0.12)	0.79 (−0.51, 2.11)
Next Four Weeks	−3.55 (−4.57, −2.53)	1.15 (−0.07, 2.37)
Tropical Cyclones		
First Two Weeks	0.88 (−1.11, 2.91)	0.78 (−1.51, 3.11)
Next Four Weeks	0.93 (−0.97, 2.87)	−1.28 (−3.40, 0.88)
Winter Storms		
First Two Weeks	4.60 (2.24, 7.01)	1.29 (−1.31, 3.95)
Next Four Weeks	−0.24 (−2.40, 1.97)	0.61 (−1.86, 3.14)



Extended Data Fig. 2 | Forest plot of non-elective hospitalization relative change and difference-in-differences for affected counties in post-disaster Weeks 1-2 and Weeks 3–6 in Medicare beneficiaries exposed to a short-term NOAA NCEI billion-dollar weather disaster in the U.S. A forest plot of non-elective hospitalization relative change and difference-in-differences with 95% CI in 271,253,459 non-unique U.S. Medicare beneficiaries in 4,884 affected counties and 18,437 control counties for weeks 1-2 and 3–6 for 42 aggregated overall and each NOAA NCEI billion-dollar disaster category (floods, floods/severe storms, severe storms, tropical cyclones, winter storms). CI – 95% confidence interval (mean ± 1.96*SEM); U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information.

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Extended Data Table 1 | Characteristics of U.S. NOAA NCEI long-term billion-dollar weather and climate disasters (wildfire and drought) for affected counties for 2011–2016 that were accounted for in selection of controls

	Wildfire	**Drought**
	Affected	Affected
Number of Disasters	4	4
Average Length of Disasters (Days)	190.8	297.5
Property and Crop Damage ($USD, in Millions)	530.4	61.5
Total Counties	232	476
Average Number of Counties	58	119
Average Number of Medicare Beneficiaries Per County	16,714	15,356

U.S., United States; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; USD, United States dollar.

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Extended Data Table 2 | Number of estimated excess ED visits, non-elective hospitalizations, and deaths in Medicare beneficiaries associated with an average-sized U.S. NOAA NCEI billion-dollar weather disaster included in the study between 2011–2016 in post-disaster week 1

	Affected Counties, Baseline Rate Per 1,000 Person-days	Affected Counties, Relative Change (95% CI)	Diff-in-Diff (95% CI) (Affected RR/Control RR)	Average County Size	Average Number of Counties Affected	Number of Excess Outcomes in Average-sized Disaster in FFS Medicare Beneficiaries in Post-disaster Week 1
ED Visits						
Overall	1.89	1.09 (0.20, 1.99)	1.22 (0.20, 2.25)	14,290	116.20	268
Flood	1.83	0.13 (-3.22, 3.59)	0.71 (-3.03, 4.60)	7,112	73.43	48
Flood/Severe Storm	1.95	0.89 (-2.06, 3.94)	-2.48 (-5.63, 0.79)	14,370	97.60	N/A
Severe Storm	1.89	1.23 (0.03, 2.44)	1.19 (-0.19, 2.60)	13,784	119.68	260
Tropical Cyclone	1.92	1.69 (-0.45, 3.87)	3.67 (1.14, 6.26)	16,174	145.80	1,165
Winter Storm	1.82	0.54 (-1.90, 3.03)	2.63 (-0.24, 5.58)	21,232	173.33	1,232
Non-elective Hospitalizations						
Overall	0.62	0.44 (-0.47, 1.37)	0.75 (-0.29, 1.81)	14,290	116.20	55
Flood	0.63	-2.40 (-5.64, 0.94)	-1.30 (-4.96, 2.50)	7,112	73.43	N/A
Flood/Severe Storm	0.58	1.32 (-1.61, 4.34)	-0.22 (-3.39, 3.06)	14,370	97.60	N/A
Severe Storm	0.62	0.16 (-1.09, 1.43)	1.59 (0.13, 3.07)	13,784	119.68	115
Tropical Cyclone	0.64	-0.30 (-2.45, 1.89)	0.16 (-2.33, 2.71)	16,174	145.80	17
Winter Storm	0.65	3.79 (1.23, 6.43)	0.68 (-2.16, 3.61)	21,232	173.33	114
Mortality						
Overall	0.12	1.15 (0.01, 2.30)	1.40 (0.08, 2.74)	14,290	116.20	20
Flood	0.12	-1.67 (-6.40, 3.31)	-2.29 (-7.43, 3.13)	7,112	73.43	N/A
Flood/Severe Storm	0.13	-2.10 (-5.54, 1.47)	-0.39 (-4.31, 3.68)	14,370	97.60	N/A
Severe Storm	0.12	0.81 (-0.77, 2.42)	2.28 (0.35, 4.26)	13,784	119.68	31
Tropical Cyclone	0.11	3.00 (0.10, 5.99)	0.69 (-2.63, 4.12)	16,174	145.80	13
Winter Storm	0.13	3.35 (0.47, 6.31)	-0.65 (-3.91, 2.73)	21,232	173.33	N/A

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percent male, percent non-Hispanic White, percent eligible for Medicaid (dual status), percent in poverty, and percent of persons over 25 with a high school diploma. N/A – not applicable; estimates of excess outcomes were not calculated if the difference-in-differences effect was negative, suggesting a decrease in events. Estimates for excess outcomes are shown when the difference -in-differences effects were positive, regardless of statistical significance. U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; CI, confidence interval; RR, risk ratio; Diff-in-Diff, difference-in-differences.

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Extended Data Table 3 | Comparison of ED visits, non-elective hospitalizations, and mortality in Medicare beneficiaries in affected versus control counties for post-disaster weeks 1-2 after onset of short-term U.S. NOAA NCEI billion-dollar weather disasters

	Affected Counties, Baseline Rate Per 1,000 Person-days	Affected Counties, Relative Change (95% CI)	Control Counties, Baseline Rate Per 1,000 Person-days	Control Counties, Relative Change (95% CI)	Diff-in-diff (95% CI) (Affected RR/Control RR)
ED Visits					
Overall	1.89	1.34 (0.58, 2.10)	1.86	0.46 (0.04, 0.88)	0.88 (0.01, 1.75)
Flood	1.83	0.92 (-1.86, 3.78)	1.86	-0.12 (-1.53, 1.30)	1.04 (-2.07, 4.26)
Flood/Severe Storm	1.95	3.07 (0.55, 5.66)	1.89	3.45 (2.26, 4.66)	-0.37 (-3.06, 2.39)
Severe Storm	1.89	0.91 (-0.10, 1.94)	1.84	0.22 (-0.37, 0.80)	0.69 (-0.47, 1.88)
Tropical Cyclone	1.94	0.89 (-0.91, 2.73)	1.88	-1.05 (-2.08, 0.00)	1.96 (-0.15, 4.12)
Winter Storm	1.83	2.78 (0.64, 4.97)	1.83	0.44 (-0.74, 1.64)	2.33 (-0.11, 4.84)
Non-elective Hospitalizations					
Overall	0.63	0.26 (-0.56, 1.09)	0.61	-0.35 (-0.79, 0.10)	0.61 (-0.33, 1.56)
Flood	0.64	-2.02 (-4.81, 0.85)	0.66	-1.26 (-2.73, 0.24)	-0.78 (-3.95, 2.51)
Flood/Severe Storm	0.58	3.16 (0.46, 5.92)	0.58	2.15 (0.91, 3.40)	0.98 (-1.91, 3.97)
Severe Storm	0.62	-1.01 (-2.13, 0.12)	0.61	-1.78 (-2.40, -1.16)	0.79 (-0.51, 2.11)
Tropical Cyclone	0.64	0.88 (-1.11, 2.91)	0.61	0.10 (-1.02, 1.23)	0.78 (-1.51, 3.11)
Winter Storm	0.65	4.60 (2.24, 7.01)	0.64	3.27 (1.99, 4.56)	1.29 (-1.31, 3.95)
Mortality					
Overall	0.12	0.18 (-0.68, 1.04)	0.12	-0.61 (-1.10, -0.11)	0.79 (-0.20, 1.79)
Flood	0.12	-1.11 (-4.51, 2.42)	0.12	-2.25 (-3.76, -0.71)	1.24 (-2.57, 5.20)
Flood/Severe Storm	0.12	-1.16 (-3.89, 1.65)	0.12	-1.71 (-3.06, -0.34)	0.56 (-2.54, 3.76)
Severe Storm	0.12	-0.60 (-1.72, 0.54)	0.12	-2.00 (-2.67, -1.32)	1.43 (0.09, 2.78)
Tropical Cyclone	0.11	0.93 (-1.09, 2.99)	0.11	2.55 (1.29, 3.81)	-1.26 (-3.56, 1.11)
Winter Storm	0.14	2.14 (-0.20, 4.53)	0.13	3.17 (1.72, 4.63)	-1.00 (-3.64, 1.72)

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percent male, percent non-Hispanic White, percent eligible for Medicaid (dual status), percent in poverty, and percent of persons over 25 with a high school diploma. U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; CI, confidence interval; RR, risk ratio; Diff-in-Diff, difference-in-differences.

 https://doi.org/10.1038/s41591-024-02833-x

Extended Data Table 4 | Comparison of ED visits, non-elective hospitalizations, and mortality in Medicare beneficiaries in affected versus control counties for post-disaster weeks 3–6 after onset of short-term U.S. NOAA NCEI billion-dollar weather disasters

	Affected Counties, Baseline Rate Per 1,000 Person-days	Affected Counties, Relative Change (95% CI)	Control Counties, Baseline Rate Per 1,000 Person-days	Control Counties, Relative Change (95% CI)	Diff-in-diff (95% CI) (Affected RR/Control RR)
ED Visits					
Overall	1.91	-0.67 (-1.32, -0.02)	1.87	-0.31 (-0.67, 0.05)	-0.36 (-1.10, 0.39)
Flood	1.86	-3.82 (-6.02, -1.56)	1.87	-2.05 (-3.21, -0.87)	-1.81 (-4.34, 0.79)
Flood/Severe Storm	1.93	1.58 (-0.50, 3.70)	1.87	2.39 (1.41, 3.38)	-0.80 (-3.03, 1.49)
Severe Storm	1.88	1.10 (0.20, 2.01)	1.84	0.52 (0.01, 1.03)	0.58 (-0.45, 1.61)
Tropical Cyclone	1.99	-3.02 (-4.55, -1.46)	1.90	-1.73 (-2.61, -0.83)	-1.32 (-3.11, 0.51)
Winter Storm	1.96	-5.09 (-6.89, -3.25)	1.93	-3.96 (-4.96, -2.94)	-1.18 (-3.31, 1.00)
Non-elective Hospitalizations					
Overall	0.64	-2.71 (-3.46, -1.95)	0.62	-2.51 (-2.92, -2.11)	-0.20 (-1.07, 0.69)
Flood	0.67	-9.19 (-11.62, -6.70)	0.66	-5.40 (-6.74, -4.03)	-4.01 (-6.91, -1.03)
Flood/Severe Storm	0.58	-0.63 (-3.06, 1.85)	0.58	1.09 (-0.04, 2.24)	-1.70 (-4.34, 1.00)
Severe Storm	0.63	-3.55 (-4.57, -2.53)	0.62	-4.65 (-5.20, -4.09)	1.15 (-0.07, 2.37)
Tropical Cyclone	0.64	0.93 (-0.97, 2.87)	0.61	2.24 (1.18, 3.31)	-1.28 (-3.40, 0.88)
Winter Storm	0.67	-0.24 (-2.40, 1.97)	0.65	-0.84 (-2.00, 0.33)	0.61 (-1.86, 3.14)
Mortality					
Overall	0.12	-2.85 (-3.52, -2.16)	0.12	-3.67 (-4.05, -3.29)	0.85 (0.05, 1.67)
Flood	0.13	-6.80 (-9.29, -4.25)	0.13	-6.07 (-7.28, -4.84)	-0.78 (-3.71, 2.23)
Flood/Severe Storm	0.12	-1.85 (-4.15, 0.51)	0.12	-1.70 (-2.81, -0.59)	-0.15 (-2.73, 2.51)
Severe Storm	0.12	-4.79 (-5.65, -3.92)	0.12	-6.59 (-7.09, -6.09)	1.93 (0.86, 3.01)
Tropical Cyclone	0.11	3.40 (1.77, 5.05)	0.11	3.23 (2.24, 4.22)	0.17 (-1.67, 2.04)
Winter Storm	0.14	-1.32 (-3.29, 0.70)	0.13	-0.70 (-1.87, 0.49)	-0.62 (-2.92, 1.74)

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percent male, percent non-Hispanic White, percent eligible for Medicaid (dual status), percent in poverty, and percent of persons over 25 with a high school diploma. U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; CI, confidence interval; RR, risk ratio; Diff-in-Diff, difference-in-differences.

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Extended Data Table 5 | Comparison of ED visits, non-elective hospitalizations, and mortality in Medicare beneficiaries in affected versus control counties for the warning period, or the week before the onset of a short-term U.S. NOAA NCEI billion-dollar weather disasters (days −1 to −7)

	Affected Counties, Baseline Rate Per 1,000 Person-days	Affected Counties, Relative Change (95% CI)	Control Counties, Baseline Rate Per 1,000 Person-days	Control Counties, Relative Change (95% CI)	Diff-in-diff (95% CI) (Affected RR/Control RR)
ED Visits					
Overall	1.89	0.38 (-0.49, 1.26)	1.85	0.09 (-0.41, 0.58)	0.30 (-0.70, 1.31)
Flood	1.83	0.01 (-3.33, 3.46)	1.84	-2.45 (-4.07, -0.81)	2.52 (-1.28, 6.47)
Flood/Severe Storm	1.93	-2.01 (-4.77, 0.83)	1.88	1.03 (-0.32, 2.40)	-3.01 (-6.02, 0.10)
Severe Storm	1.89	0.11 (-1.07, 1.32)	1.84	0.35 (-0.35, 1.06)	-0.24 (-1.61, 1.15)
Tropical Cyclone	1.92	-0.12 (-2.15, 1.94)	1.87	-0.88 (-2.08, 0.34)	0.76 (-1.62, 3.19)
Winter Storm	1.84	4.07 (1.66, 6.53)	1.86	1.03 (-0.34, 2.42)	3.01 (0.26, 5.84)
Non-elective Hospitalizations					
Overall	0.62	0.01 (-0.89, 0.93)	0.61	-0.31 (-0.81, 0.19)	0.33 (-0.71, 1.37)
Flood	0.63	-1.47 (-4.68, 1.85)	0.66	-1.23 (-2.87, 0.44)	-0.24 (-3.88, 3.53)
Flood/Severe Storm	0.57	-1.15 (-4.03, 1.82)	0.58	-3.16 (-4.48, -1.82)	2.07 (-1.20, 5.46)
Severe Storm	0.62	-0.26 (-1.50, 0.99)	0.61	-0.40 (-1.11, 0.30)	0.14 (-1.29, 1.59)
Tropical Cyclone	0.64	-0.79 (-2.93, 1.40)	0.61	0.38 (-0.87, 1.65)	-1.17 (-3.62, 1.35)
Winter Storm	0.65	4.15 (1.63, 6.73)	0.64	3.01 (1.60, 4.43)	1.11 (-1.69, 3.99)
Mortality					
Overall	0.12	0.23 (-0.90, 1.37)	0.12	0.40 (-0.27, 1.07)	-0.17 (-1.47, 1.15)
Flood	0.12	0.66 (-4.16, 5.72)	0.12	3.34 (1.10, 5.63)	-2.59 (-7.69, 2.78)
Flood/Severe Storm	0.13	-3.32 (-6.71, 0.20)	0.12	-0.30 (-2.08, 1.52)	-2.51 (-6.33, 1.47)
Severe Storm	0.12	-0.25 (-1.82, 1.34)	0.12	-0.41 (-1.37, 0.55)	0.16 (-1.68, 2.04)
Tropical Cyclone	0.11	1.18 (-1.69, 4.13)	0.11	-0.14 (-1.88, 1.62)	1.15 (-2.20, 4.61)
Winter Storm	0.13	2.35 (-0.55, 5.34)	0.13	2.46 (0.61, 4.35)	-0.11 (-3.45, 3.35)

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: FFS Medicare beneficiaries per county, population of county, median household income, average age, percent male, percent non-Hispanic White, percent eligible for Medicaid (dual status), percent in poverty, and percent of persons over 25 with a high school diploma. U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; CI, confidence interval; RR, risk ratio; Diff-in-Diff, difference-in-differences.

Extended Data Table 6 | Clinical classification software (CCS) categories for ED visits in Medicare beneficiaries during the warning pre-period and warning period for U.S. NOAA NCEI billion-dollar winter storms

Warning Pre-period (days -14 to -8 before onset of disaster)		Warning Period (days -7 to -1 before onset of disaster)	
CCS Category	**% of All ED Visits**	**CCS Category**	**% of All ED Visits**
Chest pain	4.19	Chest pain	4.34
Superficial Injury	3.25	COPD	3.64
COPD	3.19	UTI	3.01
UTI	3.11	Superficial Injury	2.99
Septicemia	3.06	CHF Non-hypertensive	2.91
Pneumonia	2.9	Septicemia	2.89
CHF Non-hypertensive	2.86	Pneumonia	2.79
Abdominal Pain	2.71	Abdominal Pain	2.6
Back Problem	2.39	Dysrhythmia	2.42
Dysrhythmia	2.31	Back Problem	2.35

CCS, clinical classification software; U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; COPD, chronic obstructive pulmonary disease; UTI, urinary tract infection; CHF, congestive heart failure.

https://doi.org/10.1038/s41591-024-02833-x

Extended Data Table 7 | Comparison of quartile 4 (most impacted) ED visits, non-elective hospitalizations, and mortality in Medicare beneficiaries in affected versus control counties for the warning period (days −1 to −7) before the onset of a short-term U.S. NOAA NCEI billion-dollar weather disasters

Analyses Restricted to Quartile 4 Counties (Most Damage) Overall, Week 1 Post-Disaster					
	Affected Counties, Baseline Rate Per 1,000 Person-days	Affected Counties, Relative Change (95% CI)	Control Counties, Baseline Rate Per 1,000 Person-days	Control Counties, Relative Change (95% CI)	Diff-in-diff (95% CI) (Affected RR/ Control RR)
ED Visits	1.90	-0.97 (-2.56, 0.65)	1.83	-0.49 (-1.42, 0.44)	-0.48 (-2.32, 1.40)
Non-elective Hospitalizations	0.63	-0.90 (-2.60, 0.82)	0.62	-0.43 (-1.38, 0.54)	-0.48 (-2.42, 1.51)
Mortality	0.12	0.49 (-1.59, 2.61)	0.12	1.23 (-0.03, 2.50)	-0.73 (-3.11, 1.72)

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percent male, percent non-Hispanic White, percent eligible for Medicaid (dual status), percent in poverty, and percent of persons over 25 with a high school diploma. U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; CI, confidence interval; RR, risk ratio; Diff-in-Diff, difference-in-differences.

Extended Data Table 8 | Sensitivity analysis examining post-disaster week 1 ED visits, non-elective hospitalizations, and mortality in Medicare beneficiaries following exposure to a short-term U.S. NOAA NCEI billion-dollar weather disasters when matching based on NOAA climate region

Post-Disaster Week 1					
	Affected Counties, Baseline Rate Per 1,000 Person-days	Affected Counties, Relative Change (95% CI)	Control Counties, Baseline Rate Per 1,000 Person-days	Control Counties, Relative Change (95% CI)	Diff-in-diff (95% CI) (Affected RR/Control RR)
ED Visits	1.86	1.10 (0.22, 1.98)	1.84	-0.32 (-0.84, 0.20)	1.42 (0.40, 2.45)
Non-elective Hospitalizations	0.62	0.41 (-0.48, 1.31)	0.61	-0.59 (-1.10, -0.08)	0.85 (-0.17, 1.88)
Mortality	0.12	0.62 (-0.53, 1.79)	0.12	-0.45 (-1.16, 0.27)	1.31 (-0.05, 2.69)

A negative binomial regression model was used, with counties as the unit of analysis. The primary predictors were an indicator of whether a county was affected or control, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects (matched on RUCA codes and census region) and were adjusted for the county characteristics: population of county, median household income, average age, percent male, percent non-Hispanic White, percent eligible for Medicaid (dual status), percent in poverty, and percent of persons over 25 with a high school diploma. U.S., United States; ED, emergency department; NOAA, National Oceanic and Atmospheric Administration; NCEI, National Centers for Environmental Information; CI, confidence interval; RR, – risk ratio; Diff-in-Diff, – difference-in-differences.

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Last updated by author(s): January 18, 2024

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For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
[ ]	[X]	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
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[ ]	[X]	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
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[ ]	[X]	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
[X]	[ ]	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
[ ]	[X]	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
[X]	[ ]	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was required for data collection
Data analysis	SAS Version 9.4 (SAS Institute Inc). The SAS code is available at GitHub and can be found at https://github.com/Billion-Dollar-Weather-Medicare/ED-Hospitalizations-Mortality

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All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

Health care utilization and outcome data for all analyses were based on administrative data for fee-for-service Medicare beneficiaries. This data cannot be shared by the authors due to regulations, but it can be acquired or purchased from Centers for Medicare and Medicaid Services. The National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) data on billion-dollar weather and climate disasters is publicly available. The Spatial Hazard Events and Losses Database for the United States (SHELDUS) cannot be shared by authors due to regulations, but it can be acquired or purchased from Arizona State University.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	Information on gender is included in Table 1 and comes from Medicare files which are based on the self-reported gender in the Social Security Administration system.
Reporting on race, ethnicity, or other socially relevant groupings	Information on race/ethnicity is included in Table 1 and comes from Medicare files based on Social Security Administration data and imputation based on surnames.
Population characteristics	Information on patient characteristics is included in Table 1. Beneficiaries in affected counties were of mean age of 71.2 years, 86.5% were non-Hispanic white, 45.3% were male, and 20.6% were Medicaid eligible. Beneficiaries in control counties were of mean age of 71.1 years, 87.3% were non-Hispanic white, 45.7% were male, and 21.4% were Medicaid eligible.
Recruitment	The sample is an unbiased representation of traditional Fee-for-service Medicare beneficiaries.
Ethics oversight	Harvard T.H. Chan School of Public Health

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Life sciences study design

All studies must disclose on these points even when the disclosure is negative.

Sample size	
Data exclusions	
Replication	
Randomization	
Blinding	

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	
Research sample	
Sampling strategy	
Data collection	
Timing	
Data exclusions	
Non-participation	
Randomization	

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Observational study of the effects of billion-dollar weather disasters on mortality, ED visits, and hospitalizations
Research sample	Fee-for-service Medicare beneficiaries in affected counties and matched control counties
Sampling strategy	Complete sample
Data collection	A combination of administrative databases
Timing and spatial scale	2011-2016 in the United States
Data exclusions	Long-term disasters: droughts and wildfires
Reproducibility	Yes, from available administrative data
Randomization	No
Blinding	No

Did the study involve field work? ☐ Yes ☒ No

Field work, collection and transport

Field conditions	
Location	
Access & import/export	
Disturbance	

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Materials & experimental systems

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X	☐ Antibodies
X	☐ Eukaryotic cell lines
X	☐ Palaeontology and archaeology
X	☐ Animals and other organisms
X	☐ Clinical data
X	☐ Dual use research of concern
X	☐ Plants

Methods

n/a	Involved in the study
X	☐ ChIP-seq
X	☐ Flow cytometry
X	☐ MRI-based neuroimaging

Antibodies

Antibodies used	
Validation	

Eukaryotic cell lines

Policy information about cell lines and Sex and Gender in Research

Cell line source(s)

Authentication

Mycoplasma contamination

Commonly misidentified lines
(See ICLAC register)

Palaeontology and Archaeology

Specimen provenance

Specimen deposition

Dating methods

☐ Tick this box to confirm that the raw and calibrated dates are available in the paper or in Supplementary Information.

Ethics oversight

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Animals and other research organisms

Policy information about studies involving animals; ARRIVE guidelines recommended for reporting animal research, and Sex and Gender in Research

Laboratory animals

Wild animals

Reporting on sex

Field-collected samples

Ethics oversight

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Clinical data

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Clinical trial registration

Study protocol

Data collection

Outcomes

Dual use research of concern

Policy information about dual use research of concern

Hazards

Could the accidental, deliberate or reckless misuse of agents or technologies generated in the work, or the application of information presented in the manuscript, pose a threat to:

No	Yes	
☐	☐	Public health
☐	☐	National security
☐	☐	Crops and/or livestock
☐	☐	Ecosystems
☐	☐	Any other significant area

Experiments of concern

Does the work involve any of these experiments of concern:

No	Yes	
☐	☐	Demonstrate how to render a vaccine ineffective
☐	☐	Confer resistance to therapeutically useful antibiotics or antiviral agents
☐	☐	Enhance the virulence of a pathogen or render a nonpathogen virulent
☐	☐	Increase transmissibility of a pathogen
☐	☐	Alter the host range of a pathogen
☐	☐	Enable evasion of diagnostic/detection modalities
☐	☐	Enable the weaponization of a biological agent or toxin
☐	☐	Any other potentially harmful combination of experiments and agents

Plants

Seed stocks

Novel plant genotypes

Authentication

ChIP-seq

Data deposition

☐ Confirm that both raw and final processed data have been deposited in a public database such as GEO.

☐ Confirm that you have deposited or provided access to graph files (e.g. BED files) for the called peaks.

Data access links
May remain private before publication.

Files in database submission

Genome browser session
(e.g. UCSC)

Methodology

Replicates

Sequencing depth

Antibodies

Peak calling parameters

Data quality

Software

Flow Cytometry

Plots

Confirm that:

☐ The axis labels state the marker and fluorochrome used (e.g. CD4-FITC).

☐ The axis scales are clearly visible. Include numbers along axes only for bottom left plot of group (a 'group' is an analysis of identical markers).

☐ All plots are contour plots with outliers or pseudocolor plots.

☐ A numerical value for number of cells or percentage (with statistics) is provided.

Methodology

Sample preparation

Instrument

Software

Cell population abundance

Gating strategy

☐ Tick this box to confirm that a figure exemplifying the gating strategy is provided in the Supplementary Information.

Magnetic resonance imaging

Experimental design

Design type

Design specifications

Behavioral performance measures

Imaging type(s)

Field strength

Sequence & imaging parameters

Area of acquisition

Diffusion MRI ☐ Used ☐ Not used

Preprocessing

Preprocessing software

Normalization

Normalization template

Noise and artifact removal

Volume censoring

Statistical modeling & inference

Model type and settings

Effect(s) tested

Specify type of analysis: ☐ Whole brain ☐ ROI-based ☐ Both

Statistic type for inference

(See Eklund et al. 2016)

Correction

Models & analysis

n/a	Involved in the study
☐	☐ Functional and/or effective connectivity
☐	☐ Graph analysis
☐	☐ Multivariate modeling or predictive analysis

Functional and/or effective connectivity

Graph analysis

Multivariate modeling and predictive analysis