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Associations between community-level disaster exposure and individual-level changes in disability and risk of death for older Americans

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Abstract

Disasters occur frequently in the United States (US) and their impact on acute morbidity, mortality and short-term increased health needs has been well described. However, barring mental health, little is known about the medium or longer-term health impacts of disasters. This study sought to determine if there is an association between community-level disaster exposure and individual-level changes in disability and/or the risk of death for older Americans. Using the US Federal Emergency Management Agency's database of disaster declarations, 602 disasters occurred between August 1998 and December 2010 and were characterized by their presence, intensity,

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duration and type. Repeated measurements of a disability score (based on activities of daily living) and dates of death were observed between January 2000 and November 2010 for 18,102 American individuals aged 50 to 89 years, who were participating in the national longitudinal Health and Retirement Study. Longitudinal (disability) and time-to-event (death) data were modelled simultaneously using a ‘joint modelling’ approach. There was no evidence of an association between community-level disaster exposure and individual-level changes in disability or the risk of death. Our results suggest that future research should focus on individual-level disaster exposures, moderate to severe disaster events, or higher-risk groups of individuals.

Keywords

death; disability; disaster; Health and Retirement Study; joint model; shared parameter model; survival

INTRODUCTION

World-wide, the United States (US) has been ranked amongst the top five countries most frequently experiencing a natural disaster (1). In 2010, 738 US counties, which represent nearly one in four counties, experienced events devastating enough to qualify for a US Federal Emergency Management Agency (FEMA) disaster declaration. Most recently, FEMA reported a total of 79 major disaster declarations for 2015; during preceding years this figure reached as high as 242 (2).

Disasters have been defined as “a situation or event which overwhelms local capacity, necessitating a request to a national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering” (1). Although the psychological impacts of disasters have been widely studied (3–5), few epidemiological studies have examined the medium or longer-term health consequences of disasters beyond the realm of mental health. Clearly, disasters may result in direct injury. We hypothesized that disasters could also result in medium-term adverse health impacts through two distinct *community-level* mechanisms related to the physical (6) and social (7) environments of the community.

First, exposure to a disaster might worsen disability through the disruption of the adapted environment that individuals had crafted around themselves to mitigate physical risks for disability. Within the healthcare system, disasters may disrupt ongoing medical care for therapies ranging from daily insulin availability to longitudinal chemotherapy courses. More subtly still, disasters may strip an individual of the adaptations he or she uses to keep a physical activity limitation from becoming a social disability. For example, consider an individual with potentially limited mobility, but who through the use of assistive devices and a careful understanding of her local geography has mapped out routes without obstacles allowing her to go to the store or church. Certainly disaster debris will undo the effectiveness of these adaptations; but even after clean-up, reconstructions along the paths of her life space may present new and difficult barriers.

Second, exposure to a disaster might operate as a community-level exposure because of its wider-ranging disruption on interlocking social support networks and institutions. Because such networks are often informal, activated only upon a contingent need, or because they involve several chains of connection, we hypothesized that there might be multiple points of brittleness that are exposed to a disaster. We hypothesized that these disruptions might unmask the *social* adaptations that are the counterpart to the physical and environmental adaptations just discussed. Consider, for example, an individual who does not currently suffer from a physical activity limitation. A disaster may not physically interfere with her body or home, however, the disaster might still lead to disability if it disrupts those networks and institutions on whom she depends to maintain her good health.

Current understanding of disasters' medium or longer-term influence on disability or even death is scant and is largely based on case studies of particular types of disasters or specific to certain communities; thus generalizability is unclear (8–11). We therefore proposed to study the impact of a range of disasters across an extended time period and impacting many US communities to determine the potential association of disaster exposure and subsequent disability or death.

METHODS

We matched community-level disaster events to individual outcomes for older Americans who were participating in a representative longitudinal panel study. Individual outcomes were death and a repeated measure of (instrumental) activities of daily living, the latter being specifically a measure of functional independence, but considered as a surrogate for disability in this study. Since these two outcomes are endogenous in older people, they must be modelled together (12, 13). Since we were directly interested in both outcomes we chose to use novel statistical methodology known as joint modelling (14–16), which allowed us to simultaneously model the longitudinal disability trajectory for each individual and their associated risk of death.

Data and sample

We utilized data from the Health and Retirement Study (HRS), a longitudinal panel survey that biannually followed a representative sample of US individuals over the age of 50 years and their spouses (17). We included 18,102 individuals, aged 50 to 89 years at baseline, who were enrolled in 1998 and had at least one follow-up survey between 1st January 2000 and 30th November 2010. Baseline, for each individual, was the date on which they completed their first eligible survey. Since individuals who complete a survey in the immediate aftermath of a disaster are likely to be an unrepresentative group, a survey was considered ineligible if it occurred during the 6 months immediately following a disaster ($n = 9111$ surveys, 12%). The 1998 data were only used to identify an individual's initial county of residence (prior to baseline); county of residence was modified, if changed at each wave, and modelled as if the change happened on the day of that survey.

Disasters were identified through the FEMA Public Assistance Program database (18), which contains all disaster declarations that qualified for federal relief funding. We obtained data which included 602 unique disaster declarations, starting on 411 unique dates between

22nd August 1998 and 26th December 2010. To test our hypotheses regarding the effects of disaster as a community-level exposure, we needed to operationalize “community” in a concrete way. Disaster events were matched to individuals based on their US county of residence. County was the finest-grained level at which national data on disaster exposure could be ascertained from this FEMA database.

Variable definitions

Outcome variables—Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs) were reported at each survey wave. We formulated a score based on the sum of ADLs and IADLs. The score took integer values between 0 and 11, inclusive, with higher values corresponding to lower levels of functional independence, which we consider a surrogate for higher levels of functional disability. We refer to this measure as a disability score throughout the paper, although we recognise that ADL/IADLs do not capture all the recommended dimensions of functioning and disability that are described in the World Health Organisation’s (WHO) International Classification of Functioning, Disability and Health (ICF) framework (19).

Time-to-death was defined as time from baseline to the date of death. An individual was censored if still alive on 30th November 2010.

Exposure variables—Different representations of the time-dependent disaster exposure were considered, based on disaster presence, intensity, duration and type. Disaster presence was the simplest form of exposure variable used, and indicated whether an individual had been exposed to a disaster during the two years prior to the current observation time t . For modelling the association between disaster exposure and disability, presence was operationalized as a binary exposure: no disaster within the previous two years; or disaster within the previous two years. For modelling the association between disaster exposure and death we separated out acute and medium-term effects by defining presence as a three-level categorical exposure: no disaster within the previous two years; disaster within the previous two years but not within the previous 21 days; or disaster within the previous 21 days. A period of 21 days was deemed to be adequate for capturing the majority of deaths which would occur in the immediate aftermath of a disaster.

Disaster intensity was defined as the cumulative amount of FEMA funding for rebuilding — not upgrading — damaged public infrastructure (in millions of US dollars) received for disasters beginning within the previous two years. Each disaster event also had a duration (in days), as determined by FEMA. We created an exposure variable based on disaster duration, defined as the cumulative duration of disasters beginning within the previous two years. We categorised both disaster intensity and duration, with the non-zero part of the distribution divided into five equally-sized quantiles; cut-points for the categories are shown in Table 5.

Disaster type was a binary indicator taking value 1 if the individual experienced a disaster beginning sometime within the previous two years and that disaster was of a specific type. The types of disasters we considered, using FEMA’s own categorization, were: earthquake, fire, flood, hurricane, tornado, storm, snow, or other.

Other covariates—Age at baseline was categorised as: 50, <60; 60, <65; 65, <70; 70, <75; 75, <80; 80, <85; and 85, <90 years. Race was categorised as: white/Caucasian; black or African American; or other. Wealth was defined at baseline for each individual using their total household (individual and spouse combined) wealth (excluding housing values) (20), and categorized into ten deciles ranging from decile 1 (most wealth) to decile 10 (least wealth).

Modelling

The joint model used in the analyses consisted of two distinct submodels: a longitudinal submodel for the disability score and a survival submodel for time-to-death. The dependency between the two outcomes is specified by allowing the survival submodel to depend on the current expected value of the log disability score as determined by the longitudinal submodel. This specification implicitly models deaths as informative drop-outs in the longitudinal model, and in turns yields estimates in the survival model that correct for the discrete-time, imperfect observation of the disability function, which is truly an unobserved continuous process. Effectively, this is achieved by the simultaneous estimation of all parameters. Alternative specifications for the association structure between the two outcomes are discussed in the Web Appendix.

Longitudinal submodel—Let $y_i = \{y_{i1}, \dots, y_{in_i}\}$ denote the vector of all observed disability measurements for individual i ($i = 1, \dots, N$) where $y_{ij} = y_i(t_{ij})$ denotes a single observed disability measurement at time point t_{ij} ($j = 1, \dots, n_i$). We specified a generalised linear mixed model $y_{ij} \sim NB(\mu_i(t_{ij}), \phi)$, where $NB(\cdot)$ represents the negative binomial distribution with scale parameter ϕ , and linear predictor related to the mean via a log link function $\eta_i(t_{ij}) = \log(\mu_i(t_{ij}))$ with

$$\eta_i(t_{ij}) = \beta_0 + \beta_1 t_{ij} + \sum_a \beta_{2a} A_{ia} + \sum_g \beta_{3g} G_{ig} + \sum_r \beta_{4r} R_{ir} + \sum_w \beta_{5w} W_{iw} + \sum_a \beta_{6a} (A_{ia} t_{ij}) + \sum_d \beta_{7d} D_{ijd} + b_{1i} + b_{2i} t_{ij}$$

(1)

where A_{ia} , G_{ig} and R_{ir} are dummy variables for the baseline age, gender and race categories respectively, W_{iw} are dummy variables for the ten wealth deciles, D_{ijd} are dummy variables for the time-varying disaster exposure categories, $\boldsymbol{\beta} = (\beta_0, \dots, \beta_{7d})$ is a vector of fixed coefficients and $\mathbf{b}_i = (b_{1i}, b_{2i})$ is a vector of individual level random coefficients (intercept and slope). We assume that $\mathbf{b}_i \sim MVN(0, \boldsymbol{\Sigma})$.

Survival submodel—Let $h_i(t)$ denote the hazard of death for individual i at time t . We

$$h_i(t) = h_0(t) \exp \left(\sum_a \gamma_{1a} A_{ia} + \sum_g \gamma_{2g} G_{ig} + \sum_r \gamma_{3r} R_{ir} + \gamma_4 W_i^* + \sum_a \gamma_{5a} (A_{ia} W_i^*) + \sum_d \gamma_{6d} D_{ijd} + \alpha_1 \eta_i(t) \right) \quad (2)$$

assumed a proportional hazards model of the form where $h_0(t)$ is the baseline hazard (the hazard for an individual in the reference category of all covariates) evaluated at time t , W_i^* is a numeric variable taking integer values for each of the wealth categories from 0 (decile 1) to 9 (decile 10), $\boldsymbol{\gamma} = (\gamma_{1a}, \dots, \gamma_{6d})$ is a vector of fixed coefficients, and α_1 is a fixed coefficient known as the association parameter. Using the numeric variable W_i^* , rather than the dummy variables W_{iw} , allowed us to fit a linear trend across wealth deciles, which was more parsimonious and resulted in little difference in model fit. The baseline hazard in the survival submodel was approximated using a parametric penalised splines-based method (21).

The coefficient α_1 provides a measure of strength of the association between the longitudinal and survival processes. Disaster, the exposure of interest, is present in both the longitudinal and survival submodels and hence the regression coefficient(s) γ_{6d} provide an estimate of the so-called direct effect of disaster on death, that is, the effect not mediated by the impact of disaster on disability.

Model estimation—We took a Bayesian approach to model estimation and used the JMBayes package (21) in R 3.2.2 (22) to fit the model. JMBayes fits joint models using a Metropolis-based Markov chain Monte Carlo (MCMC) algorithm. The Web Appendix contains further details of the model estimation.

RESULTS

Descriptive statistics

Baseline characteristics—Table 1 shows baseline characteristics of the 18,102 individuals in the study cohort. The sample was relatively balanced in terms of gender (57.8% female). The majority were white/Caucasian (83.1%), with a substantial minority being black or African American (13.4%). There was large variation in individual wealth, for example, median wealth in the poorest and richest deciles, respectively, was \$400 and \$1.3 million. The mean (SD) disability score at baseline was 0.7 (1.9), with this increasing by age. There were 543 (3%) individuals with missing baseline wealth data who were excluded from the regression modelling.

Outcome data—During the study period 67,135 disability score measurements were observed, with a mean (max) of 3.8 (6) measurements per individual. Our joint model provides valid estimates under the assumption that missing disability measurements at the survey level (3601 (5.1%) surveys) are missing at random (23).

Figure 1 shows the observed disability score trajectories for all individuals, stratified by age category and whether the individual died or was censored. A LOWESS smoothed average curve is overlaid in each plot. On average, disability scores increased during follow-up with some non-linearity also evident. Older individuals had higher disability scores on average as well as having faster rates of increase in disability. Individuals who died had higher average disability scores than those who were censored, as well as faster rates of increase in disability over time. By the censoring date of 30th November 2010, 5,304 (30%) individuals had died.

Exposure data—Of the total follow up time for all individuals (148,485 person-years), approximately 45% (67,210 person-years) was spent classified as exposed to a disaster within the previous 2 years. Of the 17,559 individuals included in the regression modelling, 6,388 (37%) were exposed to a disaster within the previous 2 years at baseline. At the time of their terminating event (death or censoring) 6,911 (39%) individuals were exposed to a disaster within the previous 2 years and 16,075 (92%) individuals had experienced at least one disaster some time during the study period. The mean (max) number of disasters experienced by each individual prior to death or censoring was 3.6 (15), however, the incidence of disaster exposure differed by disaster type (Table 2). Storm, hurricane, and snow were the most frequently experienced types of disaster event. In our discussion section we discuss why we may have observed such high disaster incidence rates in this study.

Disasters types were clustered within geographical regions; for example, hurricanes were experienced by 37% of individuals (25% of person-disaster exposure events), yet 71% of those exposures occurred within just two US states. The rates of disasters were associated with individual-level baseline characteristics, in particular age and wealth (Tables S1 and S2 of Web Appendix).

Modelling

Associations between disaster exposure and disability or death—There was no evidence that the presence of a disaster within the previous 2 years was associated with any increase in disability (disability score ratio = 0.98, 95% CrI: 0.93, 1.03) (Table 3). We also found very little evidence that the presence of a disaster within the previous 2 years (but not within the previous 21 days) was associated with any increase in the risk of death (HR = 1.03, 95% CrI: 0.96, 1.11) (Table 4). There was large uncertainty around the hazard ratio associated with disaster presence in the previous 21 days (HR = 0.96, 95% CrI: 0.75, 1.21), likely due to the small number of deaths which occurred within this narrow time frame (n = 114, just 2% of the total number of deaths). There was also no evidence that the mean disability score or risk of death increased in proportion to disaster intensity or duration (Table 5); even for an individual in the uppermost disaster intensity category (FEMA spending >\$10 million) there was no evidence that the mean disability score was higher than an individual who had not been exposed to any disaster within the previous 2 years (HR = 0.99, 95% CrI: 0.90, 1.07).

Associations between baseline characteristics and disability or death—From the longitudinal submodel (Table 3) older age, less wealth, and non-white race were

associated with higher levels of disability. The estimated annual increase in disability was also higher for individuals of older ages. Gender was not associated with the estimated disability score. From the survival submodel (Table 4) older age, being male, and less wealth were associated with a higher hazard of death. The magnitude of the association between wealth and the hazard of death diminished with increasing age.

Association between disability and death—There was evidence that the estimated disability score was strongly associated with the hazard of death (Table 4). A twofold increase in the estimated disability score for an individual (equivalent to a 0.693 unit increase in the log disability score, as $\exp(0.693) = 2$) was associated with a 36% (HR = 1.36, calculated as $\exp(0.693 \times \log(1.56))$, 95% CrI: 1.29, 1.41) increase in the hazard of death, for given fixed values of the baseline covariates and disaster exposure.

Exposure to specific disaster types—Table 6 shows disability score ratios and hazard ratios associated with exposure to specific disaster types, with the binary exposure variables for each disaster type all included in a single joint model. The largest posterior means were associated with exposure to a tornado (disability score ratio = 1.20, 95% CrI: 0.86, 1.67; HR = 1.66, 95% CrI: 1.12, 2.44), however, the statistical evidence to support these associations was relatively weak (wide credible intervals), potentially owing to the fact that tornados were relatively rare (662 person-disaster events, 1% of the total). The most prevalent disaster types (storms, hurricanes, snow) did not appear to be associated with increased disability or death.

Sensitivity analysis—In a sensitivity analysis (see Web Appendix) we refitted the disaster presence joint model to the subset of individuals with a baseline disability score of 0, 1 or 2 (“low” baseline disability). We found a slight change in the estimated disability score ratio for disaster exposure, such that it was positive, but the 95% credible interval still incorporated a value of 1 (disability score ratio = 1.04, 95% CI: 0.98 to 1.10). The estimates from the survival submodel remained almost unchanged.

DISCUSSION

This study investigated the health impacts of a temporally representative sample of disasters occurring in the US, rather than considering single disaster events as case studies. We matched community-level disaster exposures for a range of disaster types (for example hurricanes, earthquakes, fires, tornados) to individuals participating in a nationally representative longitudinal study of older Americans. We found no evidence of an association between community-level disaster exposure and individual-level changes in ADL/IADL outcome, the latter being a measure of functional independence and a surrogate of disability. Similar results were obtained even when considering several different representations (presence, intensity or duration) of disaster exposure.

Nonetheless, there are important limitations to our study that need to be recognised. These are discussed in greater detail below, but in brief, they include the inability of the community-level exposure variable to accurately reflect individual-level exposure, the potential for geographical or severity misclassification of disasters when using county-level

FEMA declarations, as well as the potential insensitivity of the outcome measure to changes in disability.

It may be that, contrary to our hypotheses, the effects of disasters (with the magnitude observed during the study period) are predominantly direct physical injury, without impact on social cohesion and bonds. Alternatively, it may be that disasters do impact on health by disrupting social cohesion and bonds, but that this occurs at a level of granularity smaller than the county. Counties in the US vary dramatically in terms of both land area and population and, therefore, a disaster event is seldom large or pervasive enough to impact all individuals living in that county. In this sense, disasters may act as a community-level exposure on an individual's disability, but there was sufficient misclassification in our exposure variable such that we could not detect an effect.

There are also several possible mechanisms by which individuals or communities may find themselves resilient to the impacts of disasters (24). Social cohesion, for example, may help to accelerate the recovery process following a disaster, or may prevent a community from becoming fragmented at the time of the event. Pre-disaster social support networks have been found to reduce the risk of adverse mental health outcomes following a disaster for individuals of low socioeconomic status (25) and the elderly (7). It is possible that social support networks are similarly protective against the medium-term physical health impacts of disasters for older people.

One of the strengths of this study was the disaster surveillance design. This led to a broadly defined exposure variable which incorporated a range of disaster types. In contrast with most studies in the literature, which consider single disaster events, our study design can provide novel insight into the wider impact of disasters on health outcomes. However, the generality of our exposure means it is difficult to compare our results directly with those from previous studies. Our exposure variable may have also been subject to misclassification. The incidence of disaster exposure was very high in this study. It may be that the FEMA definition of a disaster is too broad to be meaningful in this context. Less severe events, for example snow storms, may have attracted federal financial assistance but may not have caused the “great damage, destruction and human suffering” (1) necessary to impact on the disablement process of individuals living in the affected community. This has important implications for the interpretation of our findings, since although our results showed no association between community-level disaster exposure and disability or death across a broad range of disaster exposures, it cannot be inferred that specific disaster events do not have long-term impacts on disability. It would be unreasonable to conclude that communities, or all subgroups within a community, are resilient to the long-term impacts of all disasters based on our study. Nonetheless, we found no evidence of an association between disaster exposure and disability even when considering a graded exposure variable, such as disaster intensity or duration.

Our analyses did not adjust for county-level clustering which may have led to standard errors which were slightly narrow — which would bias *away* from the null, reinforcing the lack of statistical association in our study. In a sensitivity analysis we reran the joint model for disaster presence also including dummy variables for each US state of residence. We found

the width of the 95% credible intervals for the estimated effects of disaster exposure on either disability or death were almost unchanged. Our analyses also assumed that individuals remained in the same county of residence between surveys, potentially introducing some misclassification of disaster exposures. However, the number of misclassifications is likely to be small since, for example, 16,028 (91%) individuals in our analysis were residing in the same US state at all surveys (including the 1998 wave) and, furthermore, 93.5% of all community-dwelling respondents in the HRS lived in the same metropolitan statistical area as at their prior wave, suggesting participants in the HRS are a relatively non-transient population. Lastly, since we did not have data on clinical or self-reported diagnoses of comorbidities we were not able to adjust for individual-level comorbidities in the regression analyses.

Although the sum of ADLs and IADLs has been widely used as a measure of disability, there are several limitations to this outcome measure that are worth highlighting. First, it is recognised that the sum of ADLs and IADLs is likely to suffer from construct under-representation when used as a measure of disability (26). This refers to the fact that the ADL/IADL measure is likely to capture only part of the disability construct that we are truly interested in. That is, the sum of ADLs and IADLs is likely to provide only an imperfect measure of functional disability, and is more likely to provide a measure of functional independence. Second, a measure based on ADLs and IADLs is likely to exhibit differential item functioning, especially with regards to age (26–28). This suggests that the response probabilities for specific ADL and IADL items may be affected by age-related characteristics of the individual that are not related to the underlying disability level. Whether this leads to the sum of ADLs and IADLs being a biased measure of the severity of disability is however uncertain (26, 28).

The analyses in this study were based on novel statistical methodology, known as joint modelling. Joint models have been widely discussed in the statistical literature in the last decade (29–32), yet their presence within the epidemiological literature remains limited. The slow uptake of joint modelling methods in the epidemiological literature is likely a consequence of their recent development, their higher degree of complexity compared with standard regression methods, and their only very recent availability in mainstream statistical software. Our study highlights the usefulness of these methods for epidemiological research. We anticipate that joint models will become more widely adopted by epidemiologists now that implementations are increasingly available for standard statistical software packages (30).

In conclusion, this study found no evidence of an association between community-level disaster exposure and individual-level changes in either disability or the risk of death. Nonetheless, due to the limitations of the exposure variable, these findings should not be used as a basis for policy decisions regarding the long-term assistance provided to disaster-affected communities. Rather, our findings suggest that future research should focus on individual-level disaster exposures, moderate to severe events or disasters of a common type, and potentially consider a focus on higher-risk groups of individuals within the community.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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- Large nationally representative sample of older Americans
- Temporally representative sample of disasters occurring in the US
- Community-level disasters not associated with individual-level change in disability
- Considers disaster presence, intensity, duration and type
- Uses novel methodology for joint modelling of longitudinal and survival data

Figure 1. Observed disability score trajectories for all individuals stratified by age category and whether the individual was censored or died. The red line overlaid in the plots is the LOWESS smoothed average.

Table 1

Baseline characteristics of the study cohort.

Characteristic	Estimate
Total number of individuals	18102
Age at baseline (in years), n (%)	
50, <60	4000 (22.1%)
60, <65	3580 (19.8%)
65, <70	3256 (18.0%)
70, <75	2526 (14.0%)
75, <80	2188 (12.1%)
80, <85	1610 (8.9%)
85, <90	942 (5.2%)
Gender, n (%)	
Female	10507 (58.0%)
Race, n (%)	
White/Caucasian	14933 (82.5%)
Black or African American	2518 (13.9%)
Other	651 (3.6%)
Wealth at baseline by decile (in USD thousands), median (min, max) ^a	
Decile 1 (most wealth)	1324.0 (857, 90708)
Decile 2	636.0 (495, 856)
Decile 3	398.6 (325, 494)
Decile 4	268.4 (223, 325)
Decile 5	187.0 (156, 223)
Decile 6	128.3 (105, 156)
Decile 7	83.6 (66, 105)
Decile 8	51.0 (36, 66)
Decile 9	20.0 (6, 36)
Decile 10 (least wealth)	0.4 (0, 6)
Disability score at baseline, mean (SD)	
Stratified by age at baseline (in years)	
50, <60	0.4 (1.3)
60, <65	0.5 (1.4)
65, <70	0.6 (1.6)
70, <75	0.6 (1.7)
75, <80	0.9 (2.1)
80, <85	1.5 (2.6)
85, <90	2.6 (3.4)
Overall	0.8 (1.9)

USD, United States dollars; SD, standard deviation.

^aThere were 543 (3%) individuals with missing wealth data at baseline.

Table 2

Number of individuals experiencing each disaster type at least once, as well as the total number of person-disaster events for each disaster type.

Disaster type	Number of individuals experiencing this disaster type at least once (%)	Number of person-disaster events (%)
Storm	12944 (74%)	28894 (45.2%)
Hurricane	6415 (37%)	16090 (25.2%)
Snow	5496 (31%)	10436 (16.3%)
Fire	3229 (18%)	4291 (6.7%)
Flood	1083 (6%)	1294 (2.0%)
Tornado	662 (4%)	662 (1.0%)
Earthquake	259 (1%)	259 (0.4%)
Other	1943 (11%)	1943 (3.0%)

Notes. The 'storm' category includes severe storm, severe ice storm or coastal storm. The 'other' category includes dam/levee break, freezing, terrorist or not otherwise specified. The percentages shown are: % of total individuals (left column) and % of total person-disaster events (right column).

Table 3

Disability score ratios from longitudinal submodel of the fitted joint model for disaster presence. Estimates presented are the posterior means and 95% credible intervals.

	Disability score ratio	95% credible interval
Constant	0.02	0.02, 0.03
Time (years)	1.03	1.01, 1.04
Age category (ref: 50, <60y)		
60, <65y	0.92	0.82, 1.03
65, <70y	1.19	1.06, 1.33
70, <75y	1.72	1.51, 1.95
75, <80y	3.04	2.66, 3.48
80, <85y	5.70	4.96, 6.64
85, <90y	9.75	8.12, 11.79
Age category * time interaction		
60, <65y	1.05	1.03, 1.06
65, <70y	1.10	1.08, 1.11
70, <75y	1.18	1.16, 1.20
75, <80y	1.22	1.20, 1.24
80, <85y	1.27	1.25, 1.30
85, <90y	1.27	1.24, 1.30
Gender (ref: Male)		
Female	1.02	0.95, 1.09
Race (ref: White or Caucasian)		
Black or African American	1.30	1.17, 1.44
Other	1.15	0.95, 1.37
Wealth category (ref: Decile 1, most wealth)		
Decile 2	1.10	0.94, 1.30
Decile 3	1.27	1.08, 1.49
Decile 4	1.74	1.49, 2.05
Decile 5	1.86	1.61, 2.17
Decile 6	2.23	1.91, 2.60
Decile 7	3.06	2.60, 3.57
Decile 8	3.71	3.16, 4.32
Decile 9	5.28	4.46, 6.18
Decile 10, least wealth	9.52	8.12, 11.25
Disaster exposure		
Within previous 2 years	0.98	0.93, 1.03

ref, Reference category.

Table 4

Hazard ratios from the survival submodel of the fitted joint model for disaster presence. Estimates presented are the posterior means and 95% credible intervals.

	Hazard ratio	95% credible interval
Age category (ref: 50, <60y)		
60, <65y	2.40	1.54, 3.62
65, <70y	3.58	2.52, 5.33
70, <75y	3.80	2.65, 5.59
75, <80y	5.81	4.12, 8.54
80, <85y	7.88	5.39, 11.25
85, <90y	9.88	6.65, 14.78
Gender (ref: Male)		
Female	0.60	0.56, 0.65
Race (ref: White or Caucasian)		
Black or African American	0.90	0.80, 0.99
Other	0.74	0.61, 0.92
Wealth trend across deciles		
Linear trend (0 = Decile 1; 9 = Decile 10)	1.13	1.07, 1.18
Age category * wealth trend interaction		
60, <65y	0.93	0.87, 0.99
65, <70y	0.91	0.86, 0.96
70, <75y	0.93	0.88, 0.98
75, <80y	0.91	0.86, 0.96
80, <85y	0.89	0.85, 0.94
85, <90y	0.88	0.83, 0.93
Disaster exposure		
Within previous 21 days	0.96	0.75, 1.21
Within previous 2 years, but not 21 days	1.03	0.96, 1.11
Association parameter		
Current value	1.56	1.45, 1.65

ref, Reference category.

Table 5

Disability score ratios and hazard ratios (posterior means and 95% credible intervals) associated with disaster intensity or disaster duration. Separate joint models were fit for each of the exposure variables (i.e., 2 separate joint models). To save space, parameter estimates associated with the baseline covariates (age, gender, race, wealth) have been omitted but were similar to those contained in Tables 3 and 4.

Disaster exposure variable	Range of exposure category (min to max)	Longitudinal submodel: Disability score ratios	95% credible interval	Survival submodel: Hazard ratios	95% credible interval
Disaster spending within previous 2 years (ref: \$0)					
>\$0, Quintile 1	\$892 to \$295,828	0.97	0.90, 1.03	0.96	0.85, 1.08
>\$0, Quintile 2	\$295,877 to \$1,198,329	0.97	0.90, 1.04	1.06	0.90, 1.22
>\$0, Quintile 3	\$1,203,047 to \$3,405,042	0.96	0.88, 1.03	0.99	0.85, 1.16
>\$0, Quintile 4	\$3,432,852 to \$9,906,982	1.03	0.95, 1.11	1.07	0.88, 1.27
>\$0, Quintile 5	>\$10 million	0.99	0.90, 1.07	1.07	0.93, 1.22
Total duration of disasters beginning within previous 2 years (ref: 0 days)					
>0 days, Quintile 1	1 to 6 days	0.98	0.91, 1.05	1.03	0.90, 1.17
>0 days, Quintile 2	7 to 18 days	0.97	0.90, 1.04	1.01	0.88, 1.16
>0 days, Quintile 3	19 to 34 days	0.96	0.89, 1.03	1.00	0.88, 1.12
>0 days, Quintile 4	35 to 75 days	1.00	0.91, 1.09	1.04	0.89, 1.21
>0 days, Quintile 5	80 to 289 days	1.02	0.93, 1.12	1.06	0.89, 1.26

ref, Reference category.

Table 6

Disability score ratios and hazard ratios (posterior means and 95% credible intervals) associated with different types of disasters; a single joint model was fit which included 7 dummy variables (one for each disaster type). To save space, parameter estimates associated with the baseline covariates (age, gender, race, wealth) have been omitted but were similar to those contained in Tables 3 and 4. The estimates for each disaster type are relative to a reference category of no disaster exposure (of that type) within the previous 2 years.

	Longitudinal submodel:		Survival submodel:	
	Disability score ratios	95% credible interval	Hazard ratios	95% credible interval
Disaster exposure within previous 2 years				
Storm	1.00	0.94, 1.05	1.03	0.95, 1.13
Hurricane	0.99	0.93, 1.05	1.03	0.92, 1.21
Snow	1.00	0.94, 1.07	1.05	0.91, 1.18
Fire	1.00	0.91, 1.09	0.99	0.85, 1.16
Flood	0.88	0.74, 1.05	0.73	0.43, 1.19
Tornado	1.20	0.86, 1.67	1.66	1.12, 2.44
Earthquake	0.98	0.72, 1.34	1.30	0.58, 2.53
Other	1.01	0.91, 1.11	0.95	0.74, 1.20

Notes. The 'storm' category includes severe storm, severe ice storm or coastal storm. The 'other' category includes dam/levee break, freezing, terrorist or not otherwise specified.