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Health risks of natural hazards and resilience resources: Evidence from a U. S. nationwide longitudinal study

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ABSTRACT

Background: Although natural disasters can threaten health and well-being, some people show greater resilience to their effects than others. Identifying the characteristics related to resilience has important implications for reducing the health risks in the aftermath of a disaster.
Objective: Using the Conservation of Resources Theory as a framework, we study the role of resources in moderating the adverse effects of natural disasters on people's health and coping behaviors.
Method: We match 20,658 unique individuals aged 50 or older from the 2012–2016 waves of the Health and Retirement Study to the county-level annual natural hazard data provided by the Federal Emergency Management Agency. Using individual-fixed effect models, we first model whether the experience of natural disasters can predict people's health and coping behaviors. We then explore heterogeneity in such effects by interacting individual- and county-level resilience resources with the number of natural disasters.
Results: The results show that with increased exposure to natural disasters, older adults are more likely to experience difficulties performing instrumental daily activities. They also tend to have fewer overnight hospital stays, higher out-of-pocket medical expenses, and increased alcohol dependency. However, older adults with certain socio-economic characteristics – white, higher education, higher income, and homeownership – are better able than others to mitigate any adverse health effects of natural disasters. One significant community-level resource is a robust healthcare capacity in a county with a high ratio of healthcare practitioners, where older adults are more likely to seek hospital care and have lower alcohol dependency.
Conclusions: Health resilience can be improved by strengthening community-level healthcare capacity, with a particular focus on residents with lower socio-economic resources. Failing to address healthcare provision inequalities may exacerbate health disparities.

1. Introduction

Natural disasters, by definition, can present a major threat to health and well-being. Their sudden onset can result in injury and death and impose a substantial burden on local healthcare capacities (de Goyet et al., 2006). According to Limaye et al. (2019), ten climate-related disasters in the U.S. in 2012 caused 917 deaths, 20,568 hospital admissions, and 17,857 emergency department visits. Further, the health risks associated with natural disasters are expected to grow due to an increase in frequency and severity because of climate change (Ji and Lee, 2021).

1.1. Resilience to natural hazards: a resource conservation perspective

With the growing concern about health risks due to natural disasters, promoting resilience is pivotal for disaster risk management (de Goyet et al., 2006; Sandifer and Walker, 2018). Defined as "the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events" (NRC, 2012, p.1), resilience to natural-hazard health risks derives from individual capacities "to sustain (oneself) physically, mentally, and socially" in the aftermath of large-scale disruptions (Wulff et al., 2015, p.364).

The Conservation of Resources (COR) theory provides a useful framework for understanding the adverse impact of natural disasters on health and how people cope (Freedy et al., 1992; Hobfoll and Schumm,

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2009). The theory posits that individuals feel stressed when they need to react to a situation that threatens a loss of resources (Hobfoll et al., 2011; Hou et al., 2018). The resources come in various forms, including objects (e.g., private property), conditions (e.g., health and employment), personal (e.g., traits such as optimism), and energy resources (e.g., money, energy) (Freedy et al., 1992). Although natural disasters induce stress, either directly or indirectly (Hobfoll and Schumm, 2009), people can be resilient to disasters if they are capable of maintaining good health by engaging in proactive behaviors that sustain them (Freedy et al., 1992; Hobfoll et al., 2011; Hou et al., 2018). These post-disaster health conditions and behaviors are a function of an individual's capacity and willingness to invest in resources to protect their health and/or replenish losses (Hobfoll et al., 2011).

Following exposure to a natural disaster, resilient individuals will show a desirable outcome, such as the absence of medical or psychiatric disorders (Bonanno, 2012) and quick adjustments in symptoms (Norris et al., 2009). While the aftermath of a natural disaster may, by destroying property and disrupting normal functioning, reveal significant loss in resources, evacuation and relocation to overcrowded facilities (Greenough et al., 2008) can increase the risk of psychological distress and disease outbreaks (Aitsi-Selmi et al., 2016). Moreover, disruptions in resource-use can exacerbate physical as well as mental health problems by interrupting the provision of medical and essential supplies (i.e., food, clean water, medicines). This can intensify stress by worsening troubled relationships and increasing exposure to infections (Aitsi-Selmi et al., 2016). Such health risks, compounded by an overwhelmed healthcare system (Sharp et al., 2016), may reduce the diagnosis and treatment of early symptoms (Phibbs et al., 2018). Indeed, the absence of health issues implies a resistance to the adverse impact of natural disasters (Hobfoll et al., 2011).

Being resilient also depends on how individuals recover from distress and maintain healthy functioning (Bonanno, 2012). COR posits that the loss or threatened loss of resources can lead to different coping behaviors intended to mitigate the adverse impact of a disaster (Freedy et al., 1992; Hobfoll et al., 2011; Hobfoll and Schumm, 2009). Individuals can engage in proactive coping by focusing on altering or solving problems that result from their resource loss or perceived threat of loss (Freedy et al., 1992). Those who develop health issues may adopt active healthcare routines to secure early diagnoses or manage symptoms to recover and even improve their health. Adopting healthy behaviors can also contribute to improved overall health and thus mitigate the health risk of future disasters (Lindell, 2013). Although problem solving-focused coping involves persistent motivation to deal with challenging circumstances (Freedy et al., 1992) and require substantial resource investment (Hobfoll et al., 2011), they usually lead to better outcomes such as improved health over the long term.

People can also use defensive coping to deny the threat or to disengage, mentally and behaviorally, from a stressful situation (Freedy et al., 1992; Hobfoll et al., 2011). For example, by diminishing a person's capacity (Freedy et al., 1992) to access healthcare or use medication and rehabilitation services (Hobfoll et al., 2011), an economic loss can adversely affect their health (Aitsi-Selmi et al., 2016). Loss aversion can also lead to a reluctance to use preexisting resources against future threats (Hobfoll et al., 2011). In this situation, individuals often ignore the stressful situation or adopt destructive behaviors to cope with post-disaster stress (Gautam et al., 2009; Hobfoll et al., 2011). Such behaviors include alcohol misuse and medication noncompliance (Freedy et al., 1992; Gautam et al., 2009). While such disengagement coping behaviors (Freedy et al., 1992) can help people to adapt to extreme circumstances by suppressing stress in the short term (Hobfoll et al., 2011), they are not resilient behaviors because they do not lead to resource replenishment or future hazard preparations (Freedy et al., 1992; Hobfoll and Schumm, 2009). Instead, left unchecked, they can lead to a decline in physical and mental health over the long term (Hobfoll et al., 2011).

Generally, people are more resilient to natural hazards if they do not suffer from post-traumatic pathological and psychopathological conditions (Abramson et al., 2008; Galea et al., 2007; Wickrama and Kaspar, 2007). They tend to use problem solving-focused behaviors rather than disengagement strategies (Hobfoll et al., 2011; Hou et al., 2018). COR emphasizes that a key factor for promoting post-disaster resilient trajectories lies in personal and local resources and a willingness to invest in them (Hobfoll et al., 2011); that is, the extent to which individuals pursue resilient trajectories in the aftermath of a natural disaster depends on whether they can draw on their own and community resources (Hobfoll et al., 2011).

1.2. *Resilience resources for resilient trajectories*

Resilience resources are the "predispositions or characteristics at the individual, social, or community level" that may moderate the adverse impact of natural disasters (Schetter and Dolbier, 2011, p. 639). They include psychosocial resources (i.e., optimism, social networks), socio-economic resources (i.e., wealth, social status), and other characteristics (i.e., genetic and behavioral traits) and vary among individuals and communities (Hobfoll et al., 2011). In the aftermath of a disaster, two resources are particularly salient for pursuing healthy functioning: socio-economic status (SES) at the individual-level and healthcare capacity at the community-level.

Socio-economic status (SES), such as employment, income, education, and race/ethnicity, accounts for why some individuals show more resilient trajectories than others after a disaster (Aitsi-Selmi et al., 2016; Freedy et al., 1992; Hobfoll et al., 2011; Lehnert et al., 2020; Phibbs et al., 2018). Those in higher SES are less vulnerable to resource loss (Hou et al., 2018) and have a greater capacity to prepare for and offset any adverse impact (Hobfoll et al., 2011). For example, impoverished black and Hispanic migrant communities were disproportionately affected by Hurricane Katrina and this was due, in part, to a lack of preparedness, including plans for evacuation (Donner and Rodríguez, 2008). With preparation, people with higher SES often cope with stress and health risks better than others (Lehnert et al., 2020).

To cope in disasters, SES is particularly useful for engaging in problem solving-focused behaviors (Hobfoll and Schumm, 2009; Hobfoll et al., 2011). Those with a higher SES (i.e., better personal resources) have a greater willingness and capacity to invest in and orchestrate those resources (Hobfoll et al., 2011), which are needed to manage stress and optimal health (Phibbs et al., 2018). However, adopting better healthcare routines and behaviors is contingent on affordability and knowledge about coping behaviors. Rather than investing in their health, those in a lower SES might focus on preserving their limited resources and thus have less motivation to invest in healthcare. They may pursue disengagement coping behaviors (Hobfoll et al., 2011), relying on less costly ways to reduce stress, such as alcohol or drug abuse (Freedy et al., 1992), over the short term.

Resilience resources also exist at the community-level (Cutter et al., 2014; Schetter and Dolbier, 2011), where healthcare capacity is a primary resource that enables people to maintain healthy functioning (Berkes and Ross, 2013). However, due to a loss of essential employees and infrastructure and the temporary or permanent closure of healthcare providers, healthcare services often decrease during and after a natural disaster (Runkle et al., 2012). Under such conditions, demand for healthcare increases for acute injuries and infectious diseases (Phibbs et al., 2018; Sharp et al., 2016), and medical infrastructures are often strained, leading to chronic diseases and preexisting conditions being poorly treated if treated at all (Aitsi-Selmi et al., 2016; Runkle et al., 2012). Since excess healthcare demand can persist (Sharp et al., 2016), patients may have varying levels of accessibility to services depending on their community's healthcare capacity (Berkes and Ross, 2013). Therefore, living in medically well-served communities provides better access to healthcare and thus lowers health risks in the aftermath of a disaster (Greenough and Kirsch, 2005; Phibbs et al., 2018).

1.3. This study

In Fig. 1, we develop a theoretical framework, drawing on COR, to describe how natural hazards, individual health conditions, coping behaviors, and resilience resources intersect. We hypothesize that exposure to natural hazards is likely to increase physical and psychological health conditions (H1) and affect problem solving-focused coping behaviors (H2) and disengagement coping behaviors (H3). While the effect of natural hazards on coping behaviors may depend on resources, the observed average effect, in aggregate, would reflect whether a greater portion of the population consists of more versus less resilient individuals and whether the two coping behaviors are complements or substitutes. We further examine how resilience resources moderate the relationship between natural hazards and these outcomes. We hypothesize that individuals with greater resilience resources are less likely to experience adverse physical and psychological conditions (H4), more likely to engage in problem solving-focused coping behaviors (H5), and less likely to pursue disengagement coping strategies (H6).

To test these relationships, we use data from the Health and Retirement Study (HRS), which collects a nationally representative panel sample of adults aged 50 or older. Such adults are particularly vulnerable to the adverse effects of disasters because they have decreased physical flexibility and sensory responsiveness. This may decrease their capacity to withstand and respond to natural hazard disruptions (McQuade et al., 2018). Because any deterioration in healthy functioning in older adults can be critical, older adults are particularly at risk of developing new medical conditions (Quast and Feng, 2019).

As far as we know, no study has assessed the relationship between natural hazard exposure and health-related outcomes obtained from a nationally representative sample of U.S. older adults at multiple points in time. Most previous studies relied on small samples taken from an area affected by a single incident (Abramson et al., 2008; Fitzpatrick, 2021; Galea et al., 2007; McQuade et al., 2018; Quast and Feng, 2019; Sharp et al., 2016; Wickrama and Kaspar, 2007; Wilson-Genderson et al., 2018). Examining the health risks of natural disasters more broadly can guide research into risk mitigation and policy interventions. By understanding the health risks of disasters and the resource that can help to reduce those risks, policymakers can design and deliver better policy measures for people and communities during a disaster.

2. Methods

2.1. Data and sample

To explore the effects of natural disasters on people's health, coping behaviors, and their relationship to resource resilience, we match the community-level natural hazard incidents to individual-level data. For this, we use the national longitudinal panel dataset of the 2012–2016 waves of the Health and Retirement Study (HRS), which surveyed U.S. adults aged 50 or older and their spouses (Fisher and Ryan, 2018). Our sample period includes responses collected between 2012 and 2018.

We obtained data on natural hazards from the Disaster Declarations Summaries of the OpenFEMA (Federal Emergency Management Agency) dataset. This data contains information about presidentially declared disasters by type of natural hazard and the amount of public assistance funding made to counties over time. We merge the county-level natural hazard information with the HRS respondents based on their county of residence and the survey years. The respondent's county of residence is part of the HRS's restricted data. Researchers gain access to this data only after receiving approval from the HRS.

We derive the county-level covariates from the County Health Rankings data, which were collected from the University of Wisconsin Population Health Institute. Since 2010, the institute has published annual data on community health in several domains: health behaviors (e.g., tobacco use), clinical care (e.g., access to care), socio-economic factors (e.g., education), physical environment (e.g., housing), and health outcomes (e.g., quality of life). We use data from 2012 onward to have more consistent measures across years. We also include the percentage of healthcare practitioners who diagnose, treat, and provide other healthcare supports for patients in each county, retrieved from the American Community Survey (ACS). After the data merge, our sample included 21,486 unique individuals and 45,289 observations.

2.2. Variables

Guided by our theoretical framework, we use three broadly defined outcomes: 1) psychopathological and physical conditions; 2) problem solving-focused coping, and 3) disengagement coping. *Psychopathological and physical conditions* include self-reported depression and the number of disabilities limiting the instrumental activities of daily living (IADL). We use self-reported depression as a proxy for a psychopathological condition, which is coded as one if respondents reported that they felt sad or depressed for two or more consecutive weeks, and zero otherwise. As a proxy for a decline in physical condition, the IADL

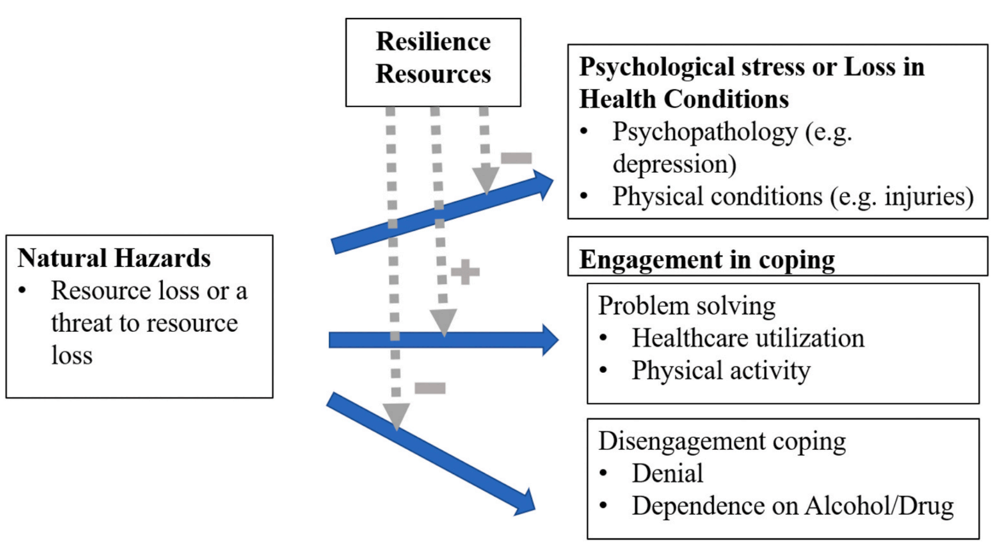

Fig. 1. Post-disaster resilience trajectory from Conservation of Resource theory.

variable counts the number of inabilities: using a map and telephone, managing money, taking medications, grocery shopping, and preparing hot meals (score 0–6).

For *problem solving-focused* coping behaviors, we consider healthcare utilization and physical activity. Healthcare utilization is measured by the number of overnight stays in hospital and out-of-pocket (OOP) medical expenditures. To address the highly skewed distribution, we take a natural logarithm transformation of the OOP medical expenditure variable to have an approximately normal distribution (Afifi et al., 2007). Our additional residual analyses provide evidence for the normality, constant variances, and homogeneity of the residuals obtained from the model where the dependent variable is log of OOP medical expenditures. We measured physical activity (PA) as vigorous sport or activity engaged in, to some degree—i.e., one to three times a month, once a week, more than once a week, every day—such as running/jogging, swimming, cycling, aerobics, gym workout, and tennis.

Disengagement coping includes alcohol dependency and the number of cigarettes smoked per day. We create a composite measure of alcohol dependency by summing four indicators of whether the respondents felt that they should reduce their drinking, were annoyed by people's criticism of their drinking, felt bad or guilty about drinking, and drank early in the morning to steady their nerves or treat a hangover (score 0–4).

To measure exposure to natural hazards, we use the *number of total disasters* that occurred in a respondent's county of residence each year. We focus on presidentially declared disasters (Brilleman et al., 2017) triggered by natural hazards such as earthquakes, tsunamis, droughts, floods, storms, and hurricanes. We consider the one-year time lag between natural hazards and individual outcomes to avoid any mismatch on the timing of the incidents, which might happen by merging the natural hazards data to the individual data based on the survey year. Through this process, we attempt to avoid counting natural hazards that occurred after the HRS participants respond to the survey. Also, as documented by Brilleman et al. (2017), outcomes measured immediately after disasters might not reflect representative behaviors and conditions.

As *resilience resources*, we include individual-level SES including education, race/ethnicity, the natural logarithm of household income, and homeownership. We also include community-level healthcare capacity measured by the percentage of healthcare practitioners (>16) and the uninsured elderly (≥65) in each county.

As time-variant individual covariates, we include age, marital status, self-reported health, employment status, number of living children, log of household income, inverse hyperbolic sine of net worth (Pence, 2006), homeownership, vehicle ownership, and health insurance. As time-variant county-level covariates, we include percentages of residents who are 65 or older, not proficient in English, African American, and live in rural areas, premature death, the average number of physically unhealthy days, percentages of smoking, obesity, heavy drinking, physical inactivity, uninsured adults, healthcare practitioners, residents with limited access to healthy food, college degree, children in poverty, number of violent crimes, log of median household income, and log of healthcare costs. We also control for year- and individual-fixed effects. All of these covariates are included in all the models. Table 1 presents the characteristics of our sample in outcomes, exposure to natural hazards, and covariates.

Table 1
Descriptive statistics on variables.

Variables	Mean (SD)	Variables	Mean (SD)
Individual-level covariates		County-level covariates	
Age	66.37 (10.85)	Premature death	7019 (1924)
Female	0.59 (0.49)	Poor/fair health	0.16 (0.04)
Educational attainment		Adult smoking	0.18 (0.04)
High school	0.52 (0.50)	Adult obesity	0.28 (0.05)
Some college	0.07 (0.25)	Excessive drinking	0.17 (0.03)
Bachelor's degree	0.16 (0.36)	Uninsured adults	0.21 (0.08)
Graduate	0.09 (0.28)	Limited access to healthy foods	0.07 (0.06)
Race/ethnicity		Healthcare workers	0.04 (0.01)
Black	0.20 (0.41)	Health care costs	9781 (1473)
Hispanic	0.14 (0.35)	Child in poverty	0.23 (0.09)
Other	0.04 (0.21)	Median household income	52,376 (13,852)
Marital status		Violent crime	449 (257)
Sep./div./wid.	0.31 (0.45)	Some college	0.62 (0.10)
Never married	0.06 (0.24)	Physical inactivity	0.24 (0.05)
Self-reported health		65 and older	0.14 (0.04)
Poor	0.05 (0.22)	African American	0.15 (0.14)
Fair	0.21 (0.37)	Not proficient in English	0.06 (0.06)
Very good	0.31 (0.39)	Rural	0.17 (0.22)
Excellent	0.09 (0.25)		
Homeowners	0.74 (0.43)	Loss in health conditions	
Health insurance owners	0.91 (0.26)	Depression	0.15 (0.32)
Car owners	0.81 (0.37)	No. of difficulty performing IALDs	0.20 (0.64)
Household income	75,161 (156,943)	Problem solving-focused coping	
Household net worth	473,303 (2,394,179)	Nights of hospital stays (if > 0)	8.10 (14.37)
Number of children	3.05 (2.05)	Out-of-pocket medical expenditures	2872 (9140)
Employment status		Vigorous physical activity	0.46 (0.44)
Employed	0.35 (0.46)	Disengagement coping	
Not working	0.09 (0.27)	Alcohol dependency	0.06 (0.50)
Natural disaster		No. of cigarettes smoked per day (if > 0)	12.24 (10.20)
Total disasters	0.31 (0.59)		

Note. 2012–2016 HRS, Unweighted. N = 21,486, obs. = 45,289. The dollar amounts are inflation-adjusted.

2.3. Empirical model

We first model to what extent changes in the number of disaster experiences predict changes in the health outcomes and coping behaviors of older adults. To this end, we adopt a difference-in-difference (DiD) design using a continuous variable (i.e., the number of disasters) as a treatment following Bleakley (2010). For overnight hospital stays and the number of cigarettes smoked, we use a fixed-effect Poisson regression model because the distribution of the variable does not approximate to normal even after the log transformation. Poisson regression models the logarithm of the expected count outcomes on various parmeters (Afifi et al., 2007). Because they drop observations with zero values of the outcome variable and measure only one time point, Poisson models use the smaller sample. For binary outcomes of depression and vigorous PA, a fixed-effect logit regression model is used. Using logit models also leads to a smaller sample because logit models drop any observations with no variations in the outcome variables across waves. For all the other outcome variables, we estimate fixed-effect linear regressions. We estimate a baseline model as follows:

$$\begin{pmatrix} H_{it} \\ log(E(H_{it}|Disaster_{ct-1}, X_{it}, C_{ct}, i_i, t_t)) \\ log\left(\frac{P(H_{it}=1)}{1-P(H_{it}=1)}\right) \end{pmatrix} = \alpha_1 Disaster_{ct-1} + \alpha_2 X_{it} + \alpha_3 C_{ct} + i_i + t_t + u_{it} \tag{1}$$

For overnight hospital stays and the number of cigarettes smoked, the log of expected counts is used to model the count as a Poisson distribution. The models for depression and vigorous PA are based on a log-odds function. $Disaster_{ct-1}$ is the number of disasters declared in year *t-1* in county *c*. H_{it} is a vector of health outcomes and coping behaviors of individual *i* in year *t*. X_{it} and C_{ct} indicate vectors of individual- and county-level characteristics measured for individual *i* who resides in county *c* in year *t*. i_i and t_t are individual- and year-fixed effects.

We also conduct additional analyses using individual random-effects models on equation (1). The DiD designs require individual fixed-effects models to explore how disasters cause changes in health outcomes before and after disasters. While this design helps to reveal how resilience resources mitigate the impact of disasters on people, natural hazards are highly correlated with space and thus may contribute to community-wide vulnerabilities over time. For example, repetitive hurricanes in the Gulf Coast can influence community-level resilience by buffering against chronic psychological and behavioral disorders. Individual fixed-effect models are less likely to capture cross-county variations in such spatial and temporal effects on health outcomes. Therefore, random effects models might have some value for understanding how natural hazards associate differently with health outcomes in individuals living in different counties. We additionally control for individual time-invariant factors such as sex, race/ethnicity and education in the random-effects models.

Furthermore, to explore more explicitly the possibility of spatial autocorrelation in health outcomes, we conduct spatial analyses. Spatial autocorrelations might be present if the value of the outcome variable of those who live in one county is a function of a weighted average of the outcome variable of those living in neighboring counties (i.e., spatial dependence) (Anselin, 2003). To explore this issue, we estimate the county-level random effects in the spatial Durbin models (SDM) that account for the spatial-autocorrelative terms (Lee and Yu, 2010). These models require a spatial weights matrix, which is the N × N matrix that calculates a geographical distance weight between the $county_i$ and the $county_j$ (Anselin, 2003). We build the spatial weight matrix using the inverse geographical distance between counties, but since our sample includes multiple individuals within a county, and the N × N county distance matrix does not allow duplicates within the same county, it is not feasible to run the SDM at the individual level. Alternatively, we create county-level data by averaging individual-level variables at the county-level in each wave. It should be noted that even though the county-level SDMs may produce results for whether natural disasters relate to county-level health outcomes via spatial mechanisms (e.g., neighboring effects, spatial clusters, etc.), due to the mismatch in their analysis units (county vs. individual) and model designs (fixed vs. random), the results are not comparable to our main results from individual-fixed effects models.

As robustness check, we test the validity of our DiD design. A causal interpretation between natural hazards and outcomes requires the exogeneity of natural hazards (Freyaldenhoven et al., 2019). The chance of experiencing a particular disaster, however, may not be random. If residents can anticipate the occurrence of a disaster, they might change their behavior accordingly before it occurs. For example, with more frequent earthquakes (Nicks, 2014), Californians might systematically differ from people living elsewhere in their awareness of health risks and consequent behaviors to prepare for them. If this anticipatory effect is prominent among people, our results could be biased. Additionally, the existence of time trends in outcomes before incidents may also result in biased estimates even though we control for time-fixed effects. To test for the presence of endogenous effects, for example, anticipatory effects and ex-ante time trends, we create a placebo treatment by shifting the number of disasters that occurred in *t-1* to pre- and post-occurrences of disasters. To do so, we use the number of disasters lagged by one-year ($lag1(Disaster_{ct-1})$and led by two-year $lead2(Disaster_{ct-1})$.

Finally, we examine the heterogeneous effects of natural hazards on outcomes according to varying levels of resilience resources using the following difference-in-difference-in-differences (DDD) design:

$$\begin{pmatrix} H_{it} \\ log(E(H_{it}|Disaster_{ct-1}, X_{it}, C_{ct}, i_i, t_t)) \\ log\left(\frac{P(H_{it}=1)}{1-P(H_{it}=1)}\right) \end{pmatrix} = \gamma_1 Disaster_{ct-1} + \gamma_2 R_{ict} + \gamma_3 Disaster_{ct-1} \times R_{ict} + \gamma_4 X_{it} + \gamma_5 C_{ct} + i_i + t_t + \varepsilon_{it} \tag{2}$$

where R_{ict} denotes proxies for resilience resources at the individual- and county-level. They include SES such as education, race/ethnicity, log of household income, and homeownership (Aitsi-Selmi et al., 2016; Freedy et al., 1992; Hobfoll et al., 2011; Lehnert et al., 2020; Phibbs et al., 2018; Schetter and Dolbier, 2011). We also consider county-level healthcare capacity by including percentages of healthcare practitioners and uninsured older adults (Cutter et al., 2014). It is worth noting that, for time-invariant proxies for resilience resources, its stand-alone variable, R_{ic}, is omitted from the models (i.e., education and race/ethnicity) because fixed-effect models difference it out via the demeaning process. However, its interaction with the disaster variable$Disaster_{ct-1} \times R_{ic}$ is not omitted due to time-varying disaster variables. The coefficient of interest is γ_3 indicating the effects of natural hazards on a particular group of individuals (characterized by R_{ict}).

3. Results

3.1. Effects of natural hazards on health outcomes of older adults

Table 2 presents the results from our baseline models. First, natural hazards are associated with the physical condition only (Panel A).

Table 2
The effect of natural hazards on health outcomes and coping behaviors.

	A. Loss in health conditions		B. Problem solving-focused coping			C. Disengagement coping	
	Depression	Difficulties performing IADLs	Nights of hospital stays	ln(OOP medical expenses)	Vigorous PA	Alcohol dependency	No. of cigarettes smoked/day
	OR (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	OR (SE)	Coef. (SE)	Coef. (SE)
(I) Fixed-effects							
No. of disasters (t-1)	1.0475	0.0089*	−0.0232**	0.0392*	0.9734	0.0027*	−0.0105
	(0.0364)	(0.0039)	(0.0078)	(0.0194)	(0.0267)	(0.0011)	(0.0081)
R-squared	NA	0.0261	NA	0.0120	NA	0.0072	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	5614
N	3056	21,486	5777	21,486	5045	21,486	2115
(II) Random-effects							
No. of disasters (t-1)	1.0526*	0.0060	−0.0298***	0.0217	0.9780	0.0027*	−0.0071
	(0.0258)	(0.0034)	(0.0074)	(0.0155)	(0.0205)	(0.0010)	(0.0079)
R-squared	NA	0.1371	NA	0.1550	NA	0.0700	NA
Obs.	45,289	45,289	45,289	45,289	45,289	45,289	45,289
N	21,486	21,486	21,486	21,486	21,486	21,486	21,486
Hausman tests χ^2	236.11***	588.70***	1613.17***	583.06***	720.91***	349.16***	525.56***
(III) County-level random effects Spatial Durbin							
No. of disasters (t-1)	0.0189	0.0200	0.1341	−0.0222	−0.0098	0.0066	0.0437
	(0.0097)	(0.0189)	(0.2119)	(0.0645)	(0.0115)	(0.0039)	(0.1048)
Spatial rho	−0.0813	−0.1875	−0.3208	0.2883	0.2031	0.1951	−0.4191
R-squared	0.1471	0.2953	0.1226	0.1979	0.2131	0.1698	0.2009
Obs.	1938	1938	1938	1938	1938	1938	1938
N	646	646	646	646	646	646	646

Note. Individual-fixed and random effects linear, logit, and Poisson regression estimators. All the covariates listed in the method section are controlled for. In the random-effects models, gender, race/ethnicity, and education are also controlled for. For the county-random effects Spatial Durbin (SDM) linear regression models, all the covariates listed in the method section are averaged across counties and waves. IADL = instrumental activities of daily living; OOP = out-of-pocket; PA = physical activity; OR = odds ratio. *p < 0.05, **p < 0.01, ***p < 0.001.

Specifically, the number of natural disasters that occurred in the prior year increases the number of inabilities restricting IADL by 0.009 units. Natural hazards also affect older adults' use of problem solving-focused behaviors by reducing hospital stays while increasing OOP medical expenses (Panel B). A one-unit increase in the number of incidents relates to decreases in the difference in the logs of expected hospital stay counts by 0.023 units, but to an increase in OOP medical expenditures by 3.9 percent. Finally, natural hazards also predict one of the disengagement coping behaviors (Panel C) by increasing the level of alcohol dependency by 0.003 units.

Since the impacts of natural hazards are estimated on multiple outcomes, we further perform a multiple testing correction to adjust the statistical significance of the natural hazard coefficients. The most widely applied method is the Bonferroni adjustments, which rely on more stringent *p*-values to reduce the positive false discovery rate (FDR) (Noble, 2009). After the Bonferroni adjustments, we find that natural hazards still remain significant for predicting changes in the nights of hospital stay and alcohol dependency at $p < 0.05$.

3.2. Additional analyses from random-effects models

According to the individual-random effect models (Panel II in Table 2), those living in counties with more natural hazards are more likely to be depressed. However, this relationship is insignificant in the fixed-effect models. If frequent disaster experiences contribute to community-wide chronic depression over the long term, the severity of depression may vary to a lesser extent over the short-term. Although natural disasters are not associated with an increased inability to

Table 3
Robustness tests, pseudo treatments.

	A. Loss in health conditions		B. Problem solving-focused coping			C. Disengagement coping	
	Depression	Difficulties performing IADLs	Nights of hospital stays	ln(OOP medical expenses)	Vigorous PA	Alcohol dependency	No. of cigarettes smoked/day
	OR (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	OR (SE)	Coef. (SE)	Coef. (SE)
(I) lag 1(No. of disaster (t-1))	0.9590	0.0042	0.0119	0.0194	0.9637	−0.0006	0.0124
	(0.0389)	(0.0044)	(0.0093)	(0.0220)	(0.0296)	(0.0012)	(0.0087)
R-squared	NA	0.0259	NA	0.0118	NA	0.0069	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	8371
N	3056	21,486	5777	21,486	5045	21,486	3056
(II) lead 2 (No. of disasters (t-1))	1.0266	−0.0007	0.0476***	0.0047	0.9931	−0.0003	0.0056
	(0.0282)	(0.0031)	(0.0061)	(0.0154)	(0.0213)	(0.0008)	(0.0066)
R-squared	NA	0.0259	NA	0.0118	NA	0.0069	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	5614
N	3056	21,486	5777	21,486	5045	21,486	2115

Note. Individual-fixed effects linear, logit, and Poisson regression estimators. All the covariates listed in the method section are controlled for. IADL = instrumental activities of daily living; OOP = out-of-pocket; PA = physical activity; OR = odds ratio. *p < 0.05, **p < 0.01, ***p < 0.001.

perform IADL or OOP medical expenses in the random-effects models, they are associated in the fixed-effects models. Disasters often have an immediate impact on IADL disabilities and OOP medical expenses, which are captured in the fixed-effects models, but their impact may not vary significantly across counties.

To explore the possible spatial autocorrelation in disaster-induced health outcomes, we further estimate county-random effects SDM (Panel III in Table 2). The spatial rho—a spatially weighted average outcome value corresponding to nearby counties—is not significant across all models, which suggests that county-level health outcomes are not spatially dependent on the health outcomes of nearby counties. After adjusting for spatial autocorrelations, we find that natural hazards are no longer associated with health outcomes and coping behaviors. The averaging process might have weakened the links between natural hazards and outcomes by aggregating variations in individual outcomes within a county.

Taken together, natural disasters may relate differently to health outcomes and coping behaviors across counties. Frequent natural disasters can reduce community-level resilience to health risks, and these impacts may not be captured in fixed-effect models. Because random-effects models are limited to "correlational" inferences, we conduct Hausman tests to check whether individual-random effects models are a correct model specification compared to individual-fixed effects models (Hausman, 1978). Since the post-estimation results support fixed-effects models, we use individual fixed-effects models for further analyses.

3.3. Robustness tests

The results that used placebo treatments suggest that the exogeneity assumption of the occurrence of natural disasters is valid (Table 3). Specifically, if other endogenous pathways (e.g., anticipatory effects) drive our results, the coefficients of the number of disasters lagged by one-years and led by two-years should be statistically significant in the same direction as $Disaster_{ct-1}$ presented in Table 2. We find that they are not correlated with most of the outcomes except for hospital overnight stays. However, coefficients for disaster variables in the model of hospital overnight stays are in the opposite direction to those in our main model, which suggests that our results are less likely to be spurious.

3.4. Moderating effects of resilience resources

To examine if the adverse effects of natural hazards vary according to resilience resources, we include the interaction term between the number of disasters in the prior year and various proxies for resilience resources. The results are presented in Table 4.

While the number of disasters increases OOP medical expenses and alcohol dependency and decreases hospital overnight stays, these relationships are moderated by higher education (Specifications I). With every additional natural hazard, higher education reduces the OOP medical expenses by 14.6–29.9 percent, alcohol dependency by 0.005–0.009 units, and increases the difference in the logs of expected hospital stay counts by 0.115–0.266 units.

We also find that non-white people are less resilient to natural hazards, especially Hispanics (Specifications II). When black people experience more natural hazards, they increase OOP medical expenditures by 11.0 percent and increase the difference in the logs of expected hospital stay counts by 0.059 units. Hispanics experiencing more natural disasters decrease the difference in the logs of expected hospital stay count by 0.249 units and exhibit elevated alcohol dependency by 0.011 units. If other racial/ethnic adults experience disasters more frequently, they reduce the difference in the logs of expected hospital stay counts by 0.262 units.

Homeowners are also more resilient to natural disasters than renters (Specifications III). While the number of disasters increases OOP medical expenditures and alcohol dependency, these adverse effects are less prevalent among homeowners. With an additional natural disaster, homeownership decreases OOP medical expenditures by 12.3 percent, alcohol dependency by 0.005, and the difference in the logs of the expected number of cigarettes smoked by 0.033.

Healthcare use and cigarette consumption by older adults with higher incomes also differ after natural disasters (Specifications IV). An increased number of disasters reduces overnight hospital stays while increasing OOP medical expenditures and the number of cigarettes smoked. However, these relationships are reversed with increased income. In response to the increased number of disasters, every 10 percent increase in household income increases the difference in the logs of the expected count of hospital stays by 0.001 units ($= 0.0194 \times \log(1.10)$) and reduces OOP medical expenditures and number of cigarettes smoked by 0.20 ($= (1.10^{-0.0212} - 1) \times 100$)and 0.18 ($= (1.10^{-0.0187} - 1) \times 100$)percent, respectively.

Related to county-level healthcare capacities, with an additional natural disaster, the increased percent of community healthcare practitioners increases the difference in the logs of the expected count of hospital stays by 7.244 units and the logs of the expected number of cigarettes smoked by 4.865 units while decreasing alcohol dependency by 0.222 units (Specification V). With more frequent disasters, a one-unit increase in the percentage of the uninsured in the community decreases the difference in the logs of the expected count of hospital stays by 0.728 units and the difference in the logs of the number of cigarettes smoked by 0.707 units (Specification VI).

4. Discussion

Taken together, our findings partially support H1 that exposure to natural disasters reduces physical health. Natural disasters often lead to losses in resources, such as economic and property loss, injury and death, and post-disaster distress and depression for those in affected areas (Fitzpatrick, 2021; Maclean et al., 2016; Wilson-Genderson et al., 2018). Large-scale disruptions to daily life and community conditions (e.g. destruction of facilities and infrastructure) also adversely affect the routines of older adults and increase their difficulty in sustaining healthy practices (e.g., taking medications and grocery shopping).

Our findings provide some evidence that exposure to natural disasters affects problem solving-focused coping behaviors (H2) while the direction of the effects is mixed. Increased exposure to natural disasters reduces the likelihood of hospital stays but increases OOP medical expenditures. An individual's diminished capacity and resources following a disaster may reduce his/her willingness to invest resources (e.g., money, time) in hospitalization (Freedy et al., 1992). Moreover, post-disaster hospitalization may be significantly affected by supporting resources at the community-level. Natural disasters strain medical infrastructures (Phibbs et al., 2018), destroy recreational facilities and spaces, and reduce access to healthy food, all of which can reduce motivations and willingness to invest resources and promote health.

The present study's findings also provide evidence for natural hazard impacts on disengagement coping (H3). With the growing number of natural disasters, people are more likely to show disengagement coping behaviors by relying on temporary stress relief, especially alcohol. The increased likelihood of unhealthy behaviors among affected individuals has been observed in previous studies, such as alcohol and nicotine dependence (Gautam et al., 2009; Maclean et al., 2016). Although our findings concerning increased alcohol dependency may provide confirmatory evidence for disengagement coping, such behaviors do not contribute to resilience in the long term (Hobfoll et al., 2011). Indeed, they are more likely to increase the health risks associated with natural disasters.

Our finding of increased OOP medical expenditures due to natural hazard exposure does not show a consistent pattern with hospital stays. Two different explanations are possible. On the one hand, older adults may increase their healthcare use other than in hospital stays after natural disaster incidents (e.g., home care or special services). On the other hand, the amount of their healthcare use may remain constant or

Table 4
Heterogeneous effects of natural hazards by resilience factors.

	A. Loss in health conditions		B. Problem solving-focused coping			C. Disengagement coping	
	Depression	Difficulties performing IADLs	Nights of hospital stays	ln(OOP medical expenses)	Vigorous PA	Alcohol dependency	No. of cigarettes smoked/day
	OR (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	OR (SE)	Coef. (SE)	Coef. (SE)
(I) No. of disasters	1.0227	0.0113	−0.1886***	0.1758***	0.9059	0.0071**	−0.0227
	(0.0677)	(0.0087)	(0.0158)	(0.0435)	(0.0531)	(0.0024)	(0.0151)
× High school	0.9994	−0.0062	0.2066***	−0.1460**	1.0930	−0.0048	0.0221
	(0.0781)	(0.0098)	(0.0182)	(0.0493)	(0.0730)	(0.0027)	(0.0172)
× Some College	1.0795	−0.0139	0.3211***	−0.2988***	1.0769	−0.0008	−0.0032
	(0.1754)	(0.0168)	(0.0342)	(0.0842)	(0.1280)	(0.0046)	(0.0409)
× Bachelor's degree	1.1097	0.0087	0.1147***	−0.1650**	1.1698	−0.0054	0.0104
	(0.1220)	(0.0121)	(0.0258)	(0.0605)	(0.1007)	(0.0033)	(0.0319)
× Graduate	1.0849	0.0004	0.2664***	−0.1761*	0.9822	−0.0091*	−0.0577
	(0.1337)	(0.0136)	(0.0259)	(0.0683)	(0.0976)	(0.0037)	(0.0416)
R-squared	NA	0.0262	NA	0.0126	NA	0.0075	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	5164
N	3056	21,486	5777	21,486	5045	21,486	2115
(II) No. of disasters	1.0387	0.0085	−0.0068	−0.0020	0.9849	0.0005	−0.0006
	(0.0480)	(0.0048)	(0.0101)	(0.0241)	(0.0346)	(0.0013)	(0.0101)
× Black	0.9626	0.0055	0.0585***	0.1095*	1.0293	0.0031	−0.0265
	(0.0737)	(0.0085)	(0.0156)	(0.0425)	(0.0610)	(0.0023)	(0.0166)
× Hispanic	1.0979	−0.0019	−0.2487***	0.0930	0.8708	0.0107***	−0.0088
	(0.0954)	(0.0108)	(0.0241)	(0.0543)	(0.0641)	(0.0030)	(0.0248)
× Other	1.0015	−0.0195	−0.2619***	0.1262	1.0492	0.0018	−0.0628
	(0.1555)	(0.0191)	(0.0412)	(0.0959)	(0.1316)	(0.0052)	(0.0441)
R-squared	NA	0.0262	NA	0.0123	NA	0.0078	NA
Obs.	8368	45,265	15,489	45,265	14,003	45,265	5612
N	3055	21,475	5776	21,475	5043	21,475	2114
(III) No. of disasters	1.0058	0.0080	−0.0125	0.1292***	0.9398	0.0062**	0.0094
	(0.0567)	(0.0068)	(0.0118)	(0.0342)	(0.0439)	(0.0019)	(0.0119)
Home owners	0.8553	−0.0694***	−0.0231	0.2103**	1.0889	0.0028	0.1839***
	(0.1088)	(0.0153)	(0.0300)	(0.0770)	(0.1107)	(0.0042)	(0.0310)
× Home owners	1.0623	0.0012	−0.0175	−0.1231**	1.0503	−0.0047*	−0.0333*
	(0.0702)	(0.0077)	(0.0144)	(0.0384)	(0.0556)	(0.0021)	(0.0146)
R-squared	NA	0.0261	NA	0.0124	NA	0.0074	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	5614
N	3056	21,486	5777	21,486	5045	21,486	2115
(IV) No. of disasters	1.1136	0.0212	−0.2237***	0.2635*	0.7830	0.0031	0.1793***
	(0.1843)	(0.0218)	(0.0534)	(0.1097)	(0.1148)	(0.0060)	(0.0393)
ln(Income)	1.0294	0.0011	−0.0197**	0.0078	0.9886	0.0006	0.0133**
	(0.0196)	(0.0024)	(0.0060)	(0.0121)	(0.0155)	(0.0007)	(0.0043)
× ln(Income)	0.9941	−0.0012	0.0194***	−0.0212*	1.0209	−0.0000	−0.0187***
	(0.0156)	(0.0020)	(0.0051)	(0.0102)	(0.0140)	(0.0005)	(0.0038)
R-squared	NA	0.0261	NA	0.0121	NA	0.0072	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	5614
N	3056	21,486	5777	21,486	5045	21,486	2115
(V) No. of disasters	1.1120	0.0047	−0.3167***	0.1764*	0.8449	0.0118**	−0.2112***
	(0.1601)	(0.0161)	(0.0316)	(0.0809)	(0.0998)	(0.0044)	(0.0342)
Healthcare workers	0.0001	1.6964*	−7.8133***	1.8809	954.7598	0.2115	−6.7929***
	(0.0008)	(0.8471)	(1.6549)	(4.2545)	(5650.6820)	(0.2319)	(1.6248)
× Healthcare workers	0.2281	0.1026	7.2443***	−3.3738	32.9572	−0.2217*	4.8652***
	(0.7879)	(0.3842)	(0.7542)	(1.9297)	(93.5113)	(0.1052)	(0.8063)
R-squared	NA	0.0261	NA	0.0121	NA	0.0456	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	5614
N	3056	21,486	5777	21,486	5045	21,486	2115
(VI) No. of disasters	1.0182	0.0162	0.1159***	−0.0393	1.0146	0.0004	0.1195***
	(0.0979)	(0.0106)	(0.0222)	(0.0534)	(0.0781)	(0.0029)	(0.0235)
Uninsured	1.6639	−0.1527	3.8149***	2.4907*	2.7881	−0.0174	−1.0404**
	(3.0004)	(0.2049)	(0.4288)	(1.0291)	(3.9603)	(0.0561)	(0.3920)
× Uninsured	1.1569	−0.0388	−0.7281***	0.4159	0.8061	0.0124	−0.7074***
	(0.5361)	(0.0525)	(0.1089)	(0.2637)	(0.3014)	(0.0144)	(0.1203)
R-squared	NA	0.0261	NA	0.0121	NA	0.0072	NA
Obs.	8371	45,289	15,492	45,289	14,008	45,289	5614
N	3056	21,486	5777	21,486	5045	21,486	2115

Note. Individual-fixed effects linear, logit, and Poisson regression estimators. All the covariates listed in the method section are controlled for. IADL = instrumental activities of daily living; OOP = out-of-pocket; PA = physical activity; OR = odds ratio. × denotes interaction terms between the number of disasters and corresponding factors. *p < 0.05, **p < 0.01, ***p < 0.001.

decrease after the disaster as seen in hospital stays, but the financial burden may increase. We support the second explanation. Overloaded healthcare systems due to acute injuries (Phibbs et al., 2018; Sharp et al., 2016) can drive older adults to seek healthcare providers outside the network and receive services not covered by insurance. These types of health services may incur greater deductibles and coinsurance for individuals even with insurance. Such financial burdens may be disproportionately greater for those who lack the necessary socio-economic resources and live in communities with limited healthcare capacities.

These findings underpin our question of how resilience resources moderate the relationship between natural disasters and these outcomes. We further examine whether those with greater resilience resources are less likely to experience adverse health conditions (H4). Our findings, in general, suggest that natural hazards exert an adverse impact on people homogeneously regardless of their SES and community conditions.

We find evidence, nevertheless, for the hypotheses that individuals with greater resilience resources are more likely to pursue problem solving-focused behaviors (H5) and less likely to use disengagement coping strategies (H6). Specifically, in the aftermath of natural hazards, the chance of older adults staying longer in hospital is increased by their education, income, and community-level healthcare capacities, such as a higher ratio of healthcare practitioners and the insured population. Our results that better educated and higher-income individuals have longer hospital stays indicate that affordability may be a key determinant in acute care utilization. Even when individuals can afford healthcare, its use is affected by the post-disaster supply of healthcare services at the community-level (Sharp et al., 2016). When multiple communities are affected by a natural disaster and simultaneously experience increased demands for healthcare services, the need for hospitalizations becomes a matter of the community's capacity to address the overload.

By contrast, alcohol abuse after a disaster is reduced among older adults with better resilience resources (i.e., higher education, homeownership, and living in a medically well-served community). Similarly, the number of cigarettes smoked is also reduced in the aftermath of a disaster among homeowners and higher-income individuals. A higher SES accompanies greater social support by community members and the capacity for better management of post-disaster stress and health (Phibbs et al., 2018). With better resources and support, older adults in higher SES may be more successful in sustaining a healthy life and, thus, less likely to develop alcohol and nicotine dependency (Aitsi-Selmi et al., 2016). Strengthening the community's healthcare capacity with a higher ratio of healthcare practitioners may also help older residents to reduce alcohol dependency. For these reasons, healthcare practitioners play an important role in building a culture of community health and helping people to use more resilient coping behaviors.

It should be noted that older adults who have experienced frequent disasters smoke more cigarettes even when they live in a highly insured community with ample healthcare workers. Although most older adults in our sample were relatively light smokers (1.65 cig/day on average), cigarette smoking can contribute to chronic conditions (Cook et al., 2020). Older adults may develop light or transitory smoking to deal with disaster-induced stress, but the new habit can increase the risk of nicotine dependence. While smoking relieves stress, it can lead to other long-term health issues. In this sense, the positive relationship between smoking and community-level healthcare capacity is counter-intuitive. Future research is warranted to deepen our understanding of this relationship.

We find inconsistent moderating effects of resilience resources on two healthcare uses. Having greater resilience resources, such as higher education and income, helps older adults to increase their hospital stays while decreasing their OOP medical expenses as exposure to natural hazards increases. As discussed earlier, under a strained healthcare capacity, older adults in a lower SES may be less capable of accessing in-network healthcare providers and, thus, bear greater financial burdens for alternative service. The economically disadvantaged and racial/ethnic minorities (Rudd et al., 2007) are likely to have lower health literacy and, thus, lower "capacity to obtain, process, communicate, and understand basic health information and services needed to make appropriate health decisions" (Ratzan and Parker, 2000, p.6). With the lack of capacities to inform complex decisions about purchasing appropriate insurance coverage, they may have difficulties understanding concepts of deductibles and coinsurance, evaluating the implications of excluded services in their coverage, and completing additional forms to enroll in supplemental plans (Martin and Parker, 2011), all of which can lead to underinsurance and an increase in OOP medical expenditures for a given service. We find similar patterns in blacks who increased hospital stays but failed to save on OOP medical expenditures after disasters. African Americans are more likely than others to visit an emergency room for non-urgent care and be denied by their insurance company for reimbursement or cost-shares (Doty and Holmgren, 2006). Therefore, individuals with fewer resilience resources may pay higher OOP medical expenses because they are underinsured or use more expensive services.

Our findings shed light on the heterogeneous coping behaviors across different races/ethnicities. With the increased occurrence of natural hazards, older Hispanic adults are less likely to pursue problem solving-focused coping (with decreased hospital stays) but more likely to use disengagement coping behaviors, especially alcohol dependence. Stronger family ties among Hispanics compared to other ethnic groups may reduce their willingness to seek help outside of kinship (Kaniasty and Norris, 1993). Hispanic culture also has a degree of fatalism insofar that many believe that they have minimal control over the environment. This leads to lower self-efficacy to control stressful events (Perilla et al., 2002). A lower self-efficacy and a lower willingness to seek social support may restrain them from pursuing proactive coping strategies and to rely instead on alcohol.

4.1. Limitations

The present study has several limitations. First, a limitation in county-level health ranking data constrained our ability to examine the health impact of natural disasters and how resilience resources moderate the health consequences of disasters in the long term. Future research may benefit by examining these relationships over an extended period (i.e., longer than six years) and further identifying the role of resilience resources in mitigating the long-term health risks associated with natural disasters. Furthermore, limited data on cigarette smoking also prevent us from identifying the underlying mechanism of counter-intuitive findings that older adults residing in medically better-served communities smoke more as they experience more disasters. An alternative measure of nicotine dependency may better capture their maladaptive coping in the aftermath of disasters, which will complement our findings.

5. Conclusion

Motivated by the COR theory, we examine how individuals are affected by and cope with natural disasters. Our study contributes to health resilience research and practice by identifying resources that help individuals to be more resilient in their post-disaster health conditions and behaviors. Improving community healthcare capacity has a greater potential to contribute to health resilience through policy interventions in the short term. Indeed, practitioners of disaster management have increasingly advocated improving healthcare capacity to reduce disaster risks, which is recognized in the Sendai Framework adopted by 187 UN member states in the 2015 United Nations World Conference on Disaster Risk Reduction (Tiernan et al., 2019; UNISDR, 2015). Accordingly, FEMA is increasingly supportive of using federal assistance funds for the restoration and protection of healthcare facilities in affected communities (Eller et al., 2018). Private healthcare providers also have a role in organizing and dispatching mobile health clinics to affected communities (Lien et al., 2014).

Our findings on heterogeneous coping behaviors among individuals according to their SES provide important implications for how to distribute healthcare resources. Strengthening healthcare capacity at the community-level should particularly benefit those who live in medically underserved communities. These resources should also be available to ensure that healthcare resources are accessible to residents with lower socio-economic resources. As our findings indicate, people of color in lower SES might reduce hospital stays but increase OOP medical expenditures regardless of their community conditions since they cannot meet the cost of their healthcare needs. A failure to account for inequality during the provision of healthcare resources may widen preexisting health and healthcare disparities (Malone et al., 2020).

Credit author statement

Su Hyupn Shin: Conceptualization, methodology, formal analysis, writing (original draft, review, & editing), Hyunjung Ji: Conceptualization, methodology, investigation, data curation, writing (original draft, review, & editing)

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