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Cascading disasters and mental health inequities: Winter Storm Uri, COVID-19 and post-traumatic stress in Texas

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ABSTRACT

Previous research on health effects of extreme weather has emphasized heat events even though cold-attributable mortality exceeds heat-attributable mortality worldwide. Little is known about the mental health effects of cold weather events, which often cascade to produce secondary impacts like power outages, leaving a knowledge gap in context of a changing climate. We address that gap by taking a novel "cascading disaster health inequities" approach to examine winter storm-associated post-traumatic stress (PTS) using survey data ($n = 790$) collected in eight Texas metro areas following Winter Storm Uri in 2021, which occurred against the backdrop of COVID-19. The incidence of storm-related PTS was 18%. Being Black (odds ratio [OR]: 6.6), Hispanic (OR: 3.5), or of another non-White race (OR: 4.2) was associated with greater odds of PTS compared to being White, which indicates substantial racial/ethnic inequities in mental health impacts (all $p < 0.05$). Having a disability also increased odds of PTS (OR: 4.4) ($p < 0.05$). Having piped water outages (OR: 1.9) and being highly impacted by COVID-19 (OR: 3.3) increased odds of PTS (both $p < 0.05$). When modelling how COVID-19 and outages cascaded, we compared householders to those with no outages and low COVID-19 impacts. PTS was more likely ($p < 0.05$) if householders had a water or power outage and high COVID-19 impacts (OR: 4.4) and if they had water and power outages and high COVID-19 impacts (OR: 7.7). Findings provide novel evidence of racial/ethnic inequities and cascading effects with regard to extreme cold events amid the COVID-19 pandemic.

1. Introduction

Three arctic fronts swept through the State of Texas (USA) from February 10 to 20, 2021. Given the moniker "Winter Storm Uri", these fronts were associated with unseasonably low temperatures. Texas' largest grid operator lost control of the power supply and 10 million people lost access to electricity (Busby et al., 2021). During the ten-day period, over 69% of Texas residents lost power and 49% lost running water for some period of time (Watson et al., 2021), and there were dramatic race-based disparities in outage duration for Black vs. White Texans (Grineski et al., 2023). The storm caused 130 billion (USD) in economic losses (Busby et al., 2021). Related power outages contributed to an estimated 700 deaths (Flores et al., 2022). Uri occurred against the backdrop of the COVID-19 pandemic, which had already disproportionately affected low-income and racial/ethnic minority communities in Texas (Ura and Garnham, 2021). In this study, we take a novel "cascading disaster health inequities" approach to examine winter storm-associated post-traumatic stress (PTS) using primary survey data collected in eight Texas metro areas following Uri.

1.1. Mental health effects of extreme weather events

Atmospheric scientists have identified causal links between anthropogenic climate change and increasingly frequent weather extremes (Otto, 2016). Global warming increases the frequency of extremely hot days and the occurrence of evaporation, which leads to drought. While the relationship between climate change and winter storms is complex (Janoski et al., 2018), warming tends to increase atmospheric moisture, resulting in more frequent extreme precipitation events, including winter storms (The National Academies Press and AuthorAnonymous, 2016).

The small literature on the health effects of extreme cold weather events has emphasized physical health rather than mental health. The Global Burden of Disease Study found that cold-attributable mortality exceeded heat-attributable mortality worldwide and that the attributable mortality rate was an order of magnitude larger for low

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temperatures than for high temperatures in the United States specifically (Burkart et al., 2021). Extreme cold weather events in Mediterranean climates were associated with spikes in mortality (Carmona et al., 2016; Antunes et al., 2017; Weilnhammer et al., 2021). Cold spells have also been associated with cardiovascular (Sartini et al., 2016; Hanefeld et al., 2019) and pulmonary morbidity in temperate climate zones (Hanefeld et al., 2019).

Extreme weather events also affect psychological well-being and mental health (Bourque and Willox, 2014), with health consequences ranging from minimal stress to clinical diagnoses like anxiety, depression, and post-traumatic stress disorder (PTSD) (U.S. Global Change Research Program, 2018). Few studies have examined mental health effects of extreme cold weather events. Review articles on climate change and mental health have tended to focus on heat waves, floods, droughts, tornados, vector-borne diseases, and wildfires, but not extreme cold weather events (Cianconi et al., 2020; Trombley et al., 2017).

Worse mental health is hypothetically associated with cold weather events for several reasons. Icy roads can worsen social isolation. Lost wages from missed work can translate into financial stress and worse mental health (Clayton et al., 2014). Mental health challenges can impair people's abilities to cope with extreme weather events. During cold weather events in the southeastern US, one-quarter of study participants reported that their mental health was at least "somewhat affected" by cold weather. White participants reported worse impacts than racial/ethnic minority participants, with 28% vs 19% respectively reporting that their mental health was at least "somewhat affected" by the cold (Mason et al., 2020).

Prior research suggests that cold weather events may impact mental health and that there may be social inequities in those impacts. Yet very limited empirical evidence is currently available. Importantly, cold weather events do not always occur in isolation; deep freezes can trigger additional impacts (e.g., power outages), which can affect human health (Casey et al., 2020).

1.2. Cascading disasters

Cascading disasters are extreme events in which progressive interactions between environmental hazards, social vulnerabilities, and infrastructure systems generate secondary events with strong subsequent impacts (Mizrahi, 2021), e.g., Janoski et al., 2018 Japan's Tōhoku earthquake and subsequent nuclear disaster (Thomas et al., 2020; Pescaroli and Alexander, 2015; Mizrahi, 2021). Specific disaster cascades are shaped by the affected place's pre-existing vulnerabilities and resilience, which can fuel or stall the progression of cascades (Pescaroli and Alexander, 2015). Thomas et al. (2020) expanded the original conception of a cascading disaster concept (Pescaroli and Alexander, 2015) to encompass the occurrence multiple causally unrelated disasters in the same place and time.

The sequence of events precipitated by the deep freeze of Winter Storm Uri constituted a cascading disaster (Clark-Ginsberg et al., 2021). While temperatures in Uri were low, 1989 was characterized by deeper cold but with fewer problems. The power outages that occurred in 2021 demonstrate how growing dependence on large technological systems creates risks of sudden interruptions to life-sustaining critical infrastructure, which are linked to specific disaster impacts (Clark-Ginsberg et al., 2021). In Uri, cascades included cold temperatures causing power and water service outages, infrastructure freeze damages (e.g., pipe bursts) resulting in sustained disruptions (as the plumbing workforce was overwhelmed), and the use of unsafe heating leading to indoor fires and carbon monoxide poisoning (Busby et al., 2021).

Uri also occurred during the COVID-19 pandemic and these two events likely cascaded to further compound suffering for Texans. As of mid-February 2021 (when Uri occurred), the US had logged 27 million cases of COVID-19 and 470,000 deaths. The vaccine rollout was in its infancy; 10.5% of the US population had received at least one dose of a COVID-19 vaccine and 3.4% had received both doses (Centers for Disease Control and Prevention, 2021). The storm delayed the deployment of 400,000 COVID-19 vaccinations in Texas (Clark-Ginsberg et al., 2021). During Uri, just under one-quarter of Texans reported social distancing less than was typical for them (Watson et al., 2021). In these ways, extant evidence suggests that the winter storm cascaded with COVID-19 to influence people's experiences during and after the storm.

1.3. Integrating a health inequities perspective

Research on the adverse health impacts of cascading disasters, and how specific disaster cascades influence particular disparate health effects, is still nascent. Despite the lack of prior research on this topic, identifying health inequities stemming from cascading disasters is critically important. Health inequities are disparities in health that are unnecessary and avoidable in addition to being unfair and unjust (Hicken et al., 2012), and include inequities related to COVID-19 (Borrell et al., 2021). Some recent work has conceptualized COVID-19 as a cascading disaster in and of itself (Mizrahi, 2021; Thomas et al., 2020). Thomas and colleagues (2020, p. 3) noted, "Since the exploration of cascading disasters is relatively new, incorporating, documenting, and assessing how marginalized groups suffer, cope, and adapt is essential for achieving environmental justice and ensuring all communities are equitably protected and included in mitigation and adaptation strategies."

This paper focuses on post-traumatic stress (PTS) as it is the most frequently studied disaster mental health outcome (Trombley et al., 2017), albeit one which has not been studied in reference to extreme cold events or from a cascading disasters perspective. Persons with PTS experience flashbacks, avoidance of stimuli that remind them of the event, hypervigilance, and/or disturbed sleep (Trombley et al., 2017).

PTS is a condition for which health inequities are well-documented. In terms of race/ethnicity, post-disaster, persons of non-White race are more likely to have PTS symptoms than White persons (Norris et al., 2002). For example, following Hurricane Katrina, Black residents disproportionately suffered from PTS symptomology relative to White residents (Davis et al., 2012, Mills et al., 2007); the same pattern occurred after Hurricane Harvey in Texas (Flores et al., 2020). When seeking to understand reasons behind racial/ethnic disparities in PTS, researchers focused on Hurricane Katrina concluded that differences in pre-hurricane mental health were partially responsible (Alexander et al., 2017). Lower socioeconomic status (Lamond et al., 2015; Gruebner et al., 2015), older age (Gruebner et al., 2015), and being a woman (Fothergill, 1996) also increase PTS risk. Health inequities in PTS following disasters or extreme weather events may be attributable in part to disability status (Stough, 2009). However, the few studies on the topic have focused on people who became disabled from a disaster and their subsequent risk of PTS (Zhou et al., 2015, Norris et al., 2010).

1.4. Contribution

This paper makes a twofold contribution to the study of disasters and health. First, we examine sociodemographic disparities in PTS after a cascading cold weather disaster. Research on cascading disasters has primarily focused on technological failures as opposed to health outcomes, neglected a health inequities perspective, and ignored cold weather events. Second, we explicitly model disaster cascades to disentangle which combination of cascades is statistically associated with the most pronounced adverse effects on PTS incidence. This approach is novel and transferrable for enhancing knowledge and formulating interventions with respect to other cascading disasters and related health disparities.

We answer the following research questions pertaining to Winter Storm Uri:

- What was the overall incidence of PTS?

- Are there social disparities in the risk of PTS?
- How did COVID-19 impacts and outages of power and water cascade to influence risk of PTS?

2. Materials and methods

2.1. Data

We collected data from Texas residents through a 35-min telephone survey conducted in English and Spanish. Professional bilingual interviewers employed by a private survey research firm conducted the interviews. They completed 11% of interviews in Spanish. This study was reviewed and declared exempt by Institutional Review Boards at the University of Utah and the University of Texas at El Paso. The survey targeted randomly selected residents in counties that comprise eight Texas Metropolitan Statistical Areas (MSAs) in July 2021 (Fig. 1). The sampling frame comprised a random sample of adults aged ≥18 years with cellular telephones in those MSAs ($n = 1964$).

To create the sampling frame, we used an address-based sampling (ABS) approach, which we augmented with a cellular phone sample. The use of ABS allowed us to oversample persons living in federally subsidized rental housing developments. In doing so, we focused on three Department of Housing and Urban Development (HUD) rental assistance programs: public housing, elderly housing (Section 202) and housing for persons with disabilities (Section 811). For the ABS component, we geolocated all HUD-assisted property addresses in each MSA and collected cell phone records from all ZIP+4 codes within a ¼ mile radius of each address, ensuring that the total number of cell phone numbers collected in each MSA was proportional to the number of HUD-assisted properties in each MSA. We then collected an equal number of records from non-HUD ZIP+4s. The cellular phone sampling component comprised cell phone records from each MSA in proportion to the total MSA population. Participants were screened for eligibility based on permanent residence in one of the eight MSAs at the time of Uri and ability to speak Spanish or English. Of 1764 eligible participants contacted, 896 took the survey, making the cooperation rate 50.8% (American Association for Public Opinion Research, 2016); 16% of those responding resided in HUD-assisted properties. To conduct the analyses reported here, we excluded respondents who were missing responses for 60% or more of our analysis variables, making the final analysis $n = 790$.

Participating respondents and their households were demographically similar to other people and households in the eight MSAs. The percentages of the population identifying as non-Hispanic White, Hispanic, and Black in the eight MSAs were respectively 38.7%, 39.7% and 12.9% (US Bureau of the Census, 2022). Among participants, those respective percentages were 42.7%, 35.4% and 10.9%. While 60.5% of households across the eight MSAs were homeowners (US Bureau of the Census, 2022), the percentage among surveyed households was 64.7%. The population-weighted median household income in the eight MSAs was $69,271 (US Bureau of the Census, 2022), which compares to $62,500 among the surveyed households.

2.2. Dependent variable

To assess PTS, we used the PTSD Checklist (PCL)-6, which is a validated short form of the 17-item PCL (Lang et al., 2012). The PCL is widely used, has good psychometric properties, and aligns with the Diagnostic and Statistical Manual of Mental Disorders criteria for PTSD

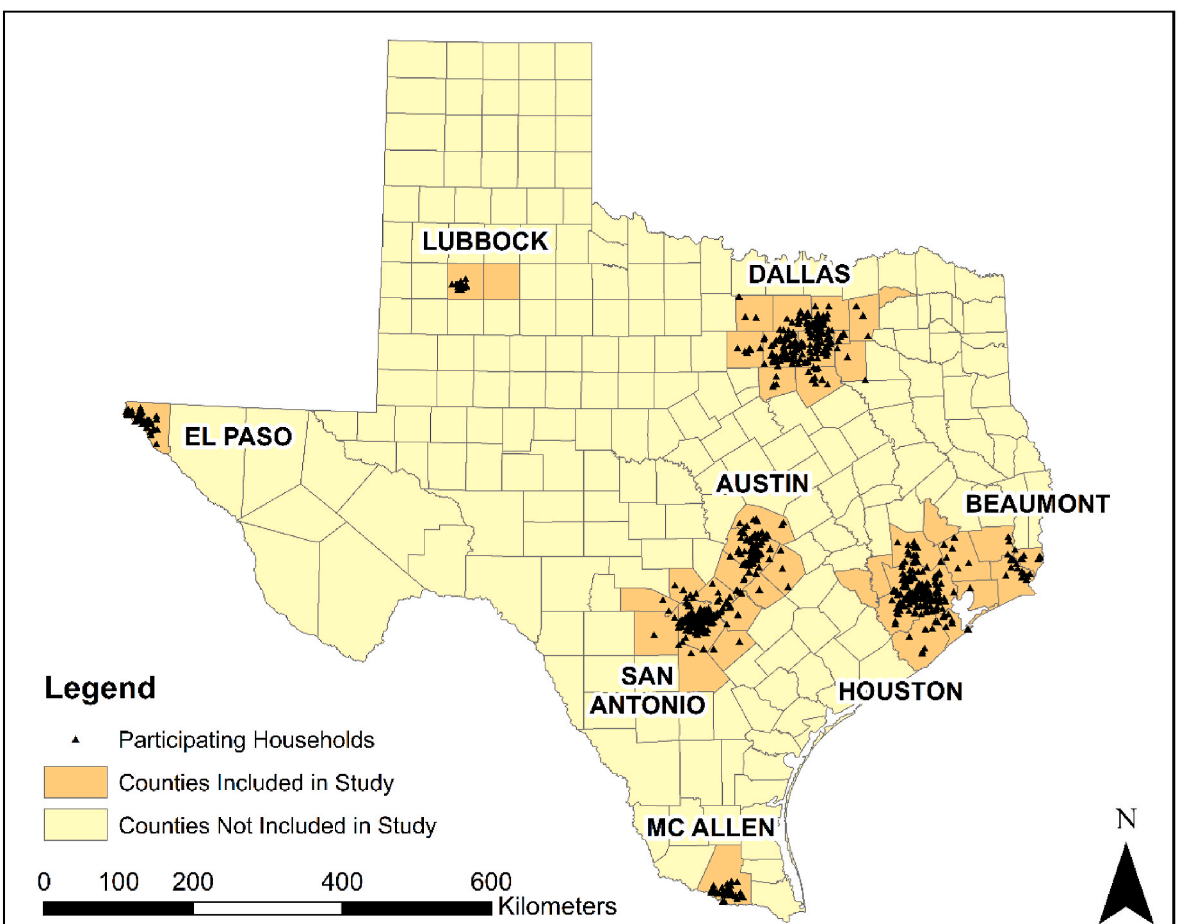

Fig. 1. Texas households participating in the July 2021 survey.

(Wilkins et al., 2011). We asked the householder about six problems they may have had at any time since the Texas Winter Storm occurred on a scale ranging from 1 (“not at all”) to 5 (“very much”) including repeated, disturbing memories, thoughts, or images of the Winter Storm and feeling very upset when something reminded you of the Winter Storm. PCL-6 scores are calculated by summing and range from 6 to 30. Those with 14 or more points are flagged as “high PTS” cases, and those with 13 or fewer points are not (Lang et al., 2012). We use this dichotomous variable since the PCL is designed to screen people for possible PTSD based on specific cutoffs (Lang et al., 2012). Table 1 reports descriptive statistics for this variable. We used the continuous PCL-6 sum score as a sensitivity analysis; the mean PCL-6 score for the 790 respondents analyzed was 9.5 (standard deviation: 5.8).

2.3. Independent variables

We used survey data to create all independent variables. There are three groups of independent variables: sociodemographic factors, disaster cascades, and control variables. Table 1 reports descriptive statistics.

2.3.1. Sociodemographic factors

We included sociodemographic variables that are associated with PTS post-disaster (Bonanno et al., 2007; Adams and Boscarino, 2006; Trombley et al., 2017). The first four gauge householder race/ethnicity, gender, older age, and disability status. We coded race/ethnicity data into Hispanic/Latino, non-Hispanic Black, and non-Hispanic person of color (POC), with non-Hispanic White as the reference category. While we asked a gender question that included “non-binary”, “genderqueer or gender non-conforming”, and “some other gender identity” as response options, all respondents selected “woman” or “man”, which we used as the reference. We coded older age as 65 and higher. We also included if the householder had a disability. We examined three variables that characterize the household, including socioeconomic status (SES; i.e., household income categories) and housing tenure (i.e., rent a HUD-assisted multifamily property, rent from a private landlord, or own, which is the reference category). We also included if the household had any children (members under 18).

2.3.2. Disaster cascades

We modeled householder exposure to cascades as a series of variables pertaining Uri and COVID-19. To account for householders’ experiences during Uri, we considered whether they experienced power and water outages, which were the most prevalent major cascades in the event (Busby et al., 2021). We asked, “Did your home lose electricity or power during the Texas Winter Storm?” and “Did your home lose piped water service in the event?” Both are yes/no questions.

We then examined if the householder had been “highly impacted” by COVID-19. We asked each respondent if the COVID-19 pandemic had impacted the following areas of their life (yes = 1/no = 0): physical health, family and close friends’ physical health, mental health, family and close friends’ mental health, finances, living conditions, employment status, immigration status, social life, ability to care for oneself or other family members, and access to health care. We summed the items. Scores ranged from 0 to 11 with the mean being 3.3. We dichotomized the variable by coding respondents with four or more “yes” responses as “highly impacted”; a similar approach was used in research that intersected COVID-19 impacts with a categorical variable (Morales et al., 2021).

We then combined the abovementioned dichotomous variables into a six-category variable that captures householders’ experiences with different combinations of cascades. The categories are: no water or power outages and low COVID-19 impacts, no water or power outages and high COVID-19 impacts, water *or* power outage and low COVID-19 impacts, water *or* power outage and high COVID-19 impacts, water *and* power outages and low COVID-19 impacts, and water *and* power outages and high COVID-19 impacts. We used the least impacted and most impacted as reference categories.

2.3.3. Control variables

We controlled for social support, prior disaster experiences, and the presence of pre-existing medical conditions. We included social support since it is a critical recovery resource post-disaster (Kaniasty, 2020) and can reduce odds of PTS (Bonanno et al., 2007). We used the 6-item F-SouzU, which is a reliable and valid scale used to assess social support in epidemiological studies (Kliem et al., 2015). Scores are calculated by summing responses to six items with higher scores corresponding to more social support. We asked, “Have you lived

Table 1
Descriptive statistics for analysis variables ($n = 790$).

	N	Yes (Valid %)	No (Valid %)	Min.	Max.	Mean	Stand. Dev.	N Missing	X Missing
High post-traumatic stress	790	142 (18.0)	648 (82.0)					0	0
Woman	758	406 (53.6)	352 (46.5)					32	4.1
White, non-Hispanic	745	318 (42.7)	427 (57.3)					45	5.7
Hispanic/Latino/x/a	749	265 (35.4)	484 (64.6)					41	5.2
Black, non-Hispanic	745	81 (10.9)	664 (89.1)					45	5.7
Other POC, non-Hispanic	745	82 (11.0)	663 (89.0)					45	5.7
Total HH income	734			1	10	5.26	2.868	56	7.1
Age 65 or more years	746	213 (28.6)	533 (71.4)					74	
With a disability	790	254 (32.2)	536 (67.8)					0	0
HH has a child (ren)									
Own	790	269 (34.1)	521 (65.9)					0	0
Rent (not HUD)	790	142 (18.0)	648 (82.0)					0	0
Rent (HUD)	790	127 (16.1)	663 (83.9)					0	0
High medical risk for COVID-19	765	312 (40.8)	453 (59.2)					25	3.2
Social support scale	774			6	30	23.88	6.958	16	2.0
Prior disaster experience									
Highly impacted by COVID-19 (4+)	766	326 (42.6)	440 (57.4)					24	3.0
Power Outage	790	592 (74.9)	198 (25.1)					0	0
Water Outage	771	362 (47.0)	409 (53.0)					19	2.4
No outages + Low COVID-19 Impacts	747	97 (13.0)	650 (87.0)					43	5.4
No outages + High COVID-19 Impacts	747	43 (5.8)	704 (94.2)					43	5.4
One outage + Low COVID-19 impacts	747	182 (24.4)	565 (75.6)					43	5.4
One outage + High COVID-19 impacts	747	122 (16.3)	625 (83.7)					43	5.4
Both outages + Low COVID-19 impacts	747	151 (20.2)	596 (79.8)					43	5.4
Both outages + High COVID-19 impacts	747	152 (20.3)	595 (79.7)					43	5.4

Note: HH = household; HUD=Housing and Urban Development; POC = persons of color.

through a disaster before the Texas Winter Storm?". We used this item because prior experience with traumatic events like natural disasters can increase odds of PTS (Bonanno et al., 2007).

We asked, "Do you have any of the following medical conditions that might put you at a higher risk for COVID?" Respondents responded "yes" or "no" to cardiovascular conditions, chronic lung disease or moderate/severe asthma, obesity, diabetes, hypertension, a weakened immune system, kidney/liver disease, and developmental/intellectual disability. Respondents were coded as 1 if they had one or more of these conditions and 0 if they had none. We focused this item on COVID-19, since the pandemic was ongoing at the time of the Winter Storm and chronic health conditions can make people more vulnerable to PTS following disasters (Bonanno et al., 2007).

2.4. Analysis methods

We began the analysis by conducting multiple imputation to address missing survey data values. This is because missing values across a set of variables can substantially reduce the sample size, statistical power and precision, as well as introduce bias if the values are not missing completely at random (Sterne et al., 2009). We used a regression-based approach to estimate 20 sets of values for each missing observation (Enders, 2010). We input 82 variables into the multiple imputation procedure, including each individual variable used to create all scales. Each set of missing values was determined through 200 iterations, and the imputed values at the maximum iteration were saved to the each of the 20 imputed datasets (Enders, 2010).

We used our multiple imputed data in stepwise multivariable generalized estimating equations (GEEs) to predict the odds of high PTS. When analyzing multiple imputed data in statistical models like GEEs, the standard errors take into account the uncertainty associated with the missing values (Rubin, 1987). GEEs expand the generalized liner model to accommodate clustered data (Liang and Zeger, 1986; Zeger and Liang, 1986; Nelder and Wedderburn, 1972). We used GEEs as our data are clustered by design (e.g., respondents in eight MSAs) and they appropriately account for non-normally distributed data (Zorn, 2001). These models assume that observations from different clusters are not correlated with each other while observations within clusters are correlated (Garson, 2012). The approach is preferable to accounting for MSA-level differences as contextual effects (e.g., as a categorical variable) as we are able to account for clustering as a nuisance parameter through model design.

We used binary logistic models due to a dichotomous dependent variable. The models use an exchangeable correlation matrix (which assumes constant intracluster dependency, so that all the off-diagonal elements of the correlation matrix are equal) and control for clustering in terms of MSA ($n = 8$) by median age of housing stock category ($n = 8$). We examined variance inflation factors, condition indices and variance proportions (Hair et al., 2013), all of which indicated the absence of multi-collinearity. We began with the sociodemographic and control variables (Model 1). In Model 2, we added the power and water outage variables. In Model 3, we added the high COVID-19 impacts variable. In Model 4, we removed the COVID-19 and outages variables and replaced them with five disaster cascade variables (reference: least exposed). In Model 5 we rotated the reference group to the most exposed to enable different comparisons. We standardized household income and social support before entering them into the GEE. Due to the oversample of HUD-residents, we applied proportional weights—constructed using total HUD population in each MSA, total population of each MSA, HUD resident population in the sample per MSA, and total sample per MSA—to the GEEs.

We conducted four sensitivity analyses. First, we ran the same set of models predicting the continuous PCL-6 sum variable (i.e., PTS severity). Those models use gamma with log link, as that was the best fitting distribution and link function. Second, we ran the same set of models without applying proportional weights. Specific to Model 2, we conducted two sensitivity analyses related to power and water outages. We substituted the duration of outage hours (in quartiles) for the dichotomous indicators of outages. Finally, we substituted five indicators for stressors associated with power and water outages for the dichotomous indicators (i.e., gastrointestinal illness; hypothermia; went without comfortable place to sleep, adequate drinking water and working toilet for some time).

3. Results

The overall incidence of "high PTS" in the entire sample was 18% (Table 1). All GEE results are summarized in Table 2. Model 1 results highlight several social disparities in PTS. All race/ethnicity variables were significant ($p < 0.001$). The odds of PTS for Black householders were 6.619 (CI: 2.872–15.256) times those of White householders. For Hispanic vs. White households, the odds ratio was 3.487 (CI 1.951–6.232) and for other POC, it was 4.239 (CI: 2.146–8.374). The odds of PTS for disabled householders were 4.397 (CI: 2.707–7.143) times those of non-disabled householders ($p < 0.001$). In terms of the control variables, a standard deviation increase on the social support scale and having prior disaster experience decreased odds of PTS by 0.712 (CI: 0.583–0.870, $p < 0.01$) and 0.557 (CI: 0.362–0.857, $p < 0.01$) times, respectively.

Model 2 shows that the odds of PTS for householders with a piped water outage during Uri were 1.949 (CI: 1.275–2.934, $p < 0.01$) times those without a water outage. While power outages were positively associated with PTS, the coefficient was not significant ($p = 0.10$). Findings for Black, Hispanic, other POC, disability, social support and disaster experience remained significant after adding power outage and piped water outage to the GEE in Model 2. The odds ratios were nearly identical to those in Model 1, suggesting that outages do not confound (weaken) or suppress (strengthen) the effects of those variables on PTS, with the exception of the Black coefficient which became nearly one point larger.

Model 3 shows that the odds of PTS are 3.265 (CI: 1.819–5.861) times higher when the householder was highly (vs. not) impacted by COVID-19 ($p < 0.001$). The five significant variables from Model 2 retained their significance, and the effect sizes were generally stable as compared to Model 2 (i.e., less than 0.2 change in odds ratio, with the exception of disability, which dropped more substantially) in Model 3.

Model 4 added all the cascades in combination. Black, Hispanic, Other POC, disability, social support, and disaster experience retained statistical significance and magnitude of effect. Respondent 65+ became significant (OR: 1.861, CI: 0.995–2.051, $p < 0.05$). Relative to those with no outages who were not highly impacted by COVID-19, the odds of a householder having PTS were 4.401 (CI: 1.513–12.803) times higher if they had one outage and high COVID impacts ($p < 0.01$). Their odds were 7.685 (CI: 2.861–20.647) times higher if they had both outages and high COVID-19 impacts ($p < 0.001$). There were no significant differences for the other comparisons.

Model 5 rotates the reference group from the least exposed to the most exposed. All coefficients, with the exception of 'one outage and high COVID-19 impacts', were significant. Those in the least exposed group had odds of PTS that were 0.130 (0.048–0.350) times lower than the most exposed ($p < 0.001$). Householders with both outages and low COVID-19 impacts had odds of PTS that were 0.293 (0.134–0.643) times lower than those with both outages and high COVID-19 impacts ($p < 0.01$). Those with one outage with low COVID-19 impacts had odds of householder PTS that were 0.166 (0.084–0.328) times lower than those with two outages with high COVID-19 impacts ($p < 0.001$). Those with no outages and high COVID-19 impacts had significantly lower risk than those with both outages and high COVID-19 impacts (OR: 0.313, CI: 0.103–0.958, $p < 0.05$).

Table 2
Results of stepwise pooled GEEs predicting odds of post-traumatic stress: sociodemographic and control variables (Model 1); adding power and water outages due to Uri (Model 2); adding COVID-19 impacts (Model 3); examining cascading impacts of Uri and COVID-19 (Model 4 and Model 5).

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Odds Ratio (95% CI)	P	Odds Ratio (95%CI)	p	Odds Ratio (95%CI)	p	Odds Ratio (95% CI)	p	Odds Ratio (95% CI)	p
Intercept	0.037 (0.016–0.082)	<0.001	0.017 (0.006–0.046)	<0.001	0.011 (0.003–0.040)	<0.001	0.013 (0.003–0.051)	<0.001	0.101 (0.035–0.291)	<0.001
Total HH income (Z score)	0.905 (0.173–4.733)	0.904	0.910 (9.006–9.046)	0.915	0.869 (9.003–9.040)	0.911	0.866 (0.068–9.051)	0.910	0.866 (9.035–11.229)	0.910
White, non-Hispanic										
Black, non-Hispanic	6.619 (2.872–15.256)	<0.001	7.427 (6.006–6.046)	<0.001	7.265 (6.003–6.040)	<0.001	7.251 (3.033–6.051)	<0.001	7.251 (6.035–17.366)	<0.001
Hispanic/Latino/x/a	3.487 (1.951–6.232)	<0.001	3.522 (4.006–4.046)	<0.001	3.455 (4.003–4.040)	<0.001	3.473 (1.758–4.051)	<0.001	3.473 (4.035–6.931)	<0.001
Other POC, non-Hispanic	4.239 (2.146–8.374)	<0.001	4.297 (2.006–2.046)	<0.001	4.188 (2.003–2.040)	<0.001	4.211 (2.189–2.051)	<0.001	4.211 (2.035–8.282)	<0.001
Age 65 or more years	1.206 (0.699–2.080)	0.500	1.366 (2.006–2.046)	0.268	1.849 (2.003–2.040)	0.052	1.861 (0.995–2.051)	0.049	1.861 (2.035–3.452)	0.049
Disability	4.397 (2.707–7.143)	<0.001	4.328 (3.006–3.046)	<0.001	3.698 (3.003–3.040)	<0.001	3.734 (2.186–3.051)	<0.001	3.734 (3.035–6.546)	<0.001
Woman	1.344 (0.961–1.880)	0.084	1.218 (3.006–3.046)	0.267	1.146 (3.003–3.040)	0.463	1.152 (0.796–3.051)	0.463	1.152 (3.035–1.680)	0.463
HH has a child (ren)	1.461 (0.947–2.255)	0.087	1.498 (4.006–4.046)	0.057	1.422 (4.003–4.040)	0.127	1.430 (0.905–4.051)	0.125	1.430 (4.035–2.258)	0.125
Own										
Rent (not HUD)	0.815 (0.456–1.455)	0.488	0.787 (8.006–8.046)	0.428	0.807 (8.003–8.040)	0.532	0.812 (0.411–8.051)	0.553	0.812 (8.035–1.616)	0.553
Rent (HUD)	1.657 (0.859–3.194)	0.132	1.932 (6.006–6.046)	0.083	2.142 (6.003–6.040)	0.068	2.084 (0.947–6.051)	0.075	2.084 (6.035–4.677)	0.075
Social support (Z score)	0.712 (0.583–0.870)	0.001	0.703 (7.006–7.046)	<0.001	0.763 (7.003–7.040)	0.020	0.762 (0.607–7.051)	0.021	0.762 (7.035–0.960)	0.021
Prior disaster experience	0.557 (0.362–0.857)	0.008	0.534 (5.006–5.046)	0.001	0.424 (5.003–5.040)	<0.001	0.425 (0.277–5.051)	<0.001	0.425 (5.035–0.651)	<0.001
High medical risk for COVID	0.936 (0.617–1.421)	0.757	1.046 (9.006–9.046)	0.826	0.919 (9.003–9.040)	0.696	0.901 (0.600–9.051)	0.642	0.901 (9.035–1.398)	0.642
Power Outage			1.635 (0.911–2.934)	0.100	1.550 (0.796–3.018)	0.197				
Water Outage			1.949 (1.275–2.934)	0.002	1.789 (1.102–2.904)	0.019				
Highly impacted by COVID (4+)					3.265 (1.819–5.861)	<0.001				
No outages + Low COVID Impacts									0.130 (0.048–0.350)	<0.001
No outages + High COVID Impacts							2.409 (0.592–9.808)	0.220	0.313 (0.103–0.958)	0.042
One outage + Low COVID impacts							1.276 (0.410–3.969)	0.674	0.166 (0.084–0.328)	<0.001
One outage + High COVID impacts							4.401 (1.513–12.803)	0.007	0.573 (0.301–1.090)	0.090
Both outages + Low COVID impacts							2.253 (0.701–7.244)	0.173	0.293 (0.134–0.642)	0.002
Both outages + High COVID impacts							7.685 (2.861–20.647)	<0.001		

Note: Models predict post-traumatic stress as a dichotomous variable based on a score of 14 or more on the PCL-6. Models use a binomial distribution, logit link function, and an exchangeable correlation matrix and account for clustering based on median age of housing stock in eight categories and metropolitan statistical area. Pooled results from 20 multiple imputed datasets are presented. REF = reference group; HH = household; HUD=Housing and Urban Development; POC = persons of color.

3.1. Sensitivity analyses

When predicting the PCL sum score, all variables indicating significant ($p < 0.05$) associations in Table 2 were also significant, with several additional significant findings. In Models 1 and 2, Children was positive and significant (Model 1 coeff: 0.064, CI: 0.005–0.124, $p < 0.05$). In Models 2 and 3, power outage was also positive and significant (Model 2 coeff: 0.121, CI: 0.049–0.193, $p < 0.01$). Model 4 had two additional findings: having one outages with low COVID-19 impacts (vs. being least exposed) was associated with greater PCL scores (coeff: 0.086, CI: 0.001–0.171), $p < 0.01$), as was having both outages with low COVID-19 impacts (coeff: 0.160, CI: 0.068–0.251, $p < 0.05$). In Model 5, there was one additional ($p < 0.05$) finding: those with one outage with high COVID-19 impacts had reduced PTS scores (coeff: −0.166, CIL-0.266 to −0.067) relative to the most exposed.

Without weights, findings were generally similar in terms of direction and significance as compared to Table 2, with a few additional findings. In Models 1 and 2, having children was significant (Model 1 OR: 1.587, CI: 1.062–2.371, $p < 0.05$). In Model 4, there were two additional positive and significant ($p < 0.05$) findings (vs. being least exposed): no outages with high COVID-19 impacts (5.706, CI: 1.556–20.932, $p < 0.01$) and one outage with low COVID-19 impacts (3.875, 1.207–12.443, $p < 0.05$).

We substituted the dichotomous outage variables in Model 2 for duration of outages and for specific impacts associated with the outages. We found that the fourth quartile for power outage duration was significant and positive relative to the first quartile (OR: 3.363, CIL 1.823–6.204, $p < 0.001$). The third quartile for water outage duration was also significant (OR: 1.724, CI: 1.107–2.685, $p < 0.05$), while fourth quartile approached significance (OR: 1.668, 0.952–2.924, $p < 0.08$) relative to the first/second quartiles (which were combined as all values were zero hours). In terms of specific impacts, we found that going without drinking water (OR: 1.997, CI: 1.188–3.359, $p < 0.01$) and going without comfortable place to sleep (OR: 2.114, CI: 1.146–3.898, $p < 0.05$) were both positive and significant risk factors for PTS, while the other impacts were not.

4. Discussion

We found that 18% of householders surveyed screened positive for PTS (i.e., probable PTSD). To the best of our knowledge, previous research has not characterized PTS after a major cold weather event, which makes it difficult to compare this percentage to those associated with similar events. However, this percentage compares to similar populations (e.g., random samples of people in affected areas) experiencing different types of disasters. The same percentage of survey respondents screened positive for PTS in Greater Houston four months after Hurricane Harvey ($n = 408$) (Flores et al., 2020). In England, 21% of survey respondents in postcodes affected by a major flood event ($n = 1925$) had 'probable PTSD' a year later (Waite et al., 2017). Among a group of older adults living 80 km west of the 2011 Tōhoku (Japan) earthquake's epicenter (n = 3567), 11% of respondents reported 'severe PTSD symptoms' 2.5 years later (Hikichi et al., 2016).

In terms of assessing social inequities in PTS, those related to race and disability were significant, while those associated with socioeconomic status, gender and age were not. The race/ethnicity and disability variables retained statistical significance ($p < 0.05$) and had odds ratios over 6 (Black), 4 (other POC), and 3 (Hispanic and disability) before and after we accounted for impacts of outages and COVID-19. These findings were robust in the sensitivity analyses. When considering the PTS severity instead of incidence in the sensitivity analysis, Black, Hispanic, and other POC householders also scored significantly higher than their White counterparts. While not previously examined in the context of extreme cold, Black and Hispanic persons experienced higher rates of adverse mental health outcomes than White persons after hurricanes and floods (Berberian et al., 2022).

Racial/ethnic minorities may be more vulnerable to the health effects of climate change, such as experiencing PTS following extreme weather events, due to underlying inequities unrelated to climate, such as systematic disinvestment and concomitantly reduced access to high quality housing, education, and food (Berberian et al., 2022). For example, these underlying inequities manifest in Black persons experiencing more negative life events and chronic stressors that affect mental health than White persons—witnessing violence, receiving bad news, loss of loved ones, major discrimination events, and daily insults (Alexander et al., 2017). As the most residentially segregated racial group in the US (Massey and Tannen, 2015), Black residents also experience poorer quality housing and neighborhoods with fewer health-enhancing resources, which may reduce their resiliency after disasters and extreme weather events (Alexander et al., 2017). We must acknowledge that the root causes of racial health inequities, like those uncovered here, are cultural and structural racism (Hicken et al., 2018). As emphasized in critical race theory, cultural and structural racism are ubiquitous and serve to favor the dominant racial group (Hicken et al., 2018). While historical pressures shape cultural processes, the historical roots of inequity are often erased (Farmer, 2004), leaving contemporary racial health inequities to appear without clear links to the structural forces that produced them (Hicken et al., 2018).

Unlike race/ethnicity, socioeconomic status, gender and age, disability is rarely examined in disaster mental health studies (Stough, 2009). Few studies have looked at disability status as a risk factor for PTS following disasters or extreme weather events, making it difficult to contextualize our findings. An online survey of persons with mobility impairments after disasters found than eight respondents (13%) reported some type of post disaster emotional trauma including fear, grief, nightmares, and generalized stress (Rooney and White, 2007). A report from a qualitative study of 18 people with disabilities after Hurricane Katrina found that all participants reported some emotional stress or depression (as cited by Stough, 2009). Stough (2009) stated, "excluding the small collection of empirical studies on individuals with preexisting psychiatric illnesses, researchers have virtually ignored the psychological effects of disaster on individuals with intellectual disabilities, physical disabilities, or sensory impairments" (p. 273). We find here that, even when adjusting for race/ethnicity, gender, and SES, those with disabilities were over three times more likely to suffer from Uri-related PTS than those without. Stough (2009) called for future research to examine mental health and disability in the context of disasters. We addressed that call here by examining disability status of respondents.

In terms of why persons with disabilities might suffer disproportionately from PTS after an extreme weather event, emergency managers may be inadequately trained to address their particular needs, leaving them unsupported. Those with independent living and/or self-care difficulties may suffer due to disruptions in the services they depend on daily. In addition to more typical stressors, they can also experience disability-specific challenges. Some individuals with visual disabilities, for example, have been separated from their assistance dogs or durable medical equipment (e.g., canes) during disaster evacuation. Persons with developmental disabilities have been distressed by emergency-related stimuli, like sirens, bells, flashing lights, strangers, and emergency personnel (Stough, 2009).

We found that water outages significantly increased risk of householder PTS. Power outages were associated with increased risk, but not significantly ($p < 0.2$). Water outages were less common than power outages during Uri and water outages lasted 10 h longer on average (Watson et al., 2021). The effects of water outages can also extend beyond the duration of the outage (e.g., needing to boil water and to reach a plumber to repair damaged pipes), perhaps making water outages more indicative of event severity, which is associated with greater risk of PTS (Quan et al., 2017). In terms of what may be driving the finding, sensitivity analyses showed that going without drinking water for some time was a significant risk factor for PTS. When looking at PTS severity, power outages emerged as *another* significant risk factor. Longer power outage duration was significantly associated with PTS risk. These sensitivity analyses suggest that aspects of power outage experiences are associated with PTS.

To our knowledge, very little research has examined public service disruptions and PTS. One study, conducted a year after major flooding in England, found that households that had been flooded and experienced domestic utilities disruption had a seven-fold higher rate of PTS than those that had only been flooded (Waite et al., 2017). Rather than examine mental health outcomes like PTS, it is more common to study physical health impacts of water and power outages (Säve-Söderbergh et al., 2017; Ercumen et al., 2014; Huang et al., 2011). Adopting a "cascading disaster health inequity" perspective draws attention to the potentially traumatic experiences associated with major utility disruptions that can follow extreme weather.

In terms of how COVID-19, power outages and water outages cascaded as correlates of PTS, we can draw several lessons. First, results show how being highly impacted by COVID-19 amplified the risks of storm-related PTS, regardless of water or power outage status. Had we examined Uri as a cascading disaster in the traditional sense (Pescaroli and Alexander, 2015) (i.e., cold temperatures causing power and water outages), we would not have considered the potential synergistic effects of COVID-19 on storm-related PTS and would have only emphasized the importance of water outages to PTS (as per Model 2). Extending from Thomas et al.'s (2020) observation that cascading disasters may encompass unrelated events that happen in the same place simultaneously, we examined possible cascades with COVID-19, some of which clearly amplified risks of PTS. This speaks to the seriousness of the pandemic as a cascading influence on mental health in association with other traumatic events, beyond the physical harms of SARS-CoV-2 infection. This also suggests that the pandemic may represent a pervasive, cascading risk factor in disaster-related health outcomes worldwide.

Second, having both outages emerged as risk factors for PTS under particular conditions. Having no water and power outages during Uri decreased risks of PTS relative to having both outages, specifically among householders who experienced high COVID-19 impacts, a finding which held when predicting PTS severity in the sensitivity analysis. In that same sensitivity analysis, among those with low COVID-19 impacts, having both outages (vs. zero outages) was associated with higher PTS severity. Findings also show dramatic differences in risks of PTS as impacts cascaded: the odds ratio was over 7.5 for the most affected householders (with both outages and high COVID-19 impacts) vs. the least affected (with no outages and low COVID-19 impacts). There are reasons why having both outages could be associated with PTS. The experience of living without power and water, which the average Texan did for over 40 and 30 h respectively (Watson et al., 2021; Grineski et al., 2023), can take its toll on mental health. Toilets cannot be flushed, indoor spaces remain dark, and food spoils in the refrigerator and freezer. Without tap water, many people did not have water to drink; 63% of Texans reported challenges accessing bottled water during Uri and 75% had difficulty obtaining groceries (Watson et al., 2021). Both types of outages are associated with increased risk of gastrointestinal illness (GII) (Ercumen et al., 2014; Marx et al., 2006). Cold temperatures indoors cause discomfort and stress and present major morbidity and mortality risks (The National Academies Press and AuthorAnonymous, 2016). It stands to reason that coping with these sequalae from outages simultaneously with COVID-19 challenges could worsen mental health.

4.1. Limitations

Since we conducted the survey five months after Uri, recall may have been difficult for some respondents. However, this analysis focuses on highly memorable events such as losing access to power. We do not know why some householders chose not to participate in the survey and if there is any non-response bias in the sample. We used the PCL to screen for PTS (probable PTSD), which does not substitute for a medical diagnosis. Our PTS measure was specific to the winter storm; we do not have a parallel measure for COVID-19-related PTS. We surveyed only English and Spanish speaking residents since two-thirds of Texans speak English at home and, of the remaining third who do not, 85% speak Spanish (Ura and McCullough, 2015). However, this approach neglects those who are not English-proficient and who speak other languages, which in Texas includes (but is not limited to) Vietnamese, Chinese, Tagalog, Hindi and Urdu (Ura and McCullough, 2015). We did not examine how sociodemographic characteristics moderated associations between the cascades and PTS. Future research with a larger sample size should investigate this, perhaps using qualitative comparative analysis (Schneider and Wagemann, 2010).

Our analysis was limited to a subset of available survey variables. We assessed prior disaster experience with only one dichotomous variable. Our models cannot elucidate many specific secondary stressors associated with water and power outages that increase risk for PTS. While some households had repeated power and/or water outages during the storm, we do not have data on the length of each outage. We also do not know if households used a generator when they lost power. Finally, we lack data on perceived discrimination and baseline trauma, which are important to understanding why racial/ethnic minority respondents suffer disproportionately from PTS (Alexander et al., 2017).

5. Conclusion

The paper contributes new knowledge on mental health inequities following extreme weather events—an understudied and important topic in the context of climate change. It highlights the usefulness of linking a health inequities perspective with research on cascading disasters. We found the overall incidence of storm-related PTS among householders was 18%. Being from a racial/ethnic minority group or having a disability more than tripled one's odds of PTS. Having a piped water outage during Uri and being highly impacted by COVID-19 also increased odds of householder PTS. With a few exceptions, COVID-19 amplified the risks of PTS by cascading with experiences of service outages. This research suggests the importance of helping householders cope with underlying COVID-19 related disruptions as part of disaster aid services and the importance of mental health support for racial/ethnic minority residents after extreme weather events.

Credit authors statement

Sara E. Grineski: Conceptualization, Methodology, Formal analysis, Writing- Original draft preparation, Funding acquisition. **Timothy W. Collins**: Conceptualization, Methodology, Writing- Reviewing and Editing, Funding acquisition. **Jayajit Chakraborty**: Conceptualization , Writing- Reviewing and Editing, Funding acquisition

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Declaration of competing interest

None.

Data availability

The data that has been used is confidential.

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