Sociodemographic factors associated with heatwave risk perception in the United States

June 26, 2023

Weather, Climate, and Society

Authors
Forrest S. Schoessow[a]
Yajie Li[a]
Jennifer R. Marlon[b]
Anthony Leiserowitz[b]
Peter D. Howe[a]*,

*Corresponding author, peter.howe@usu.edu

[a]Department of Environment and Society
Utah State University

[b]Yale Program on Climate Change Communication
Yale University

Sociodemographic factors associated with heatwave risk perception in the United States

Abstract

Extreme heat events are one of the deadliest weather-related hazards in the United States and are increasing in frequency and severity due to anthropogenic greenhouse gas emissions. Further, some subpopulations may be more vulnerable than others due to social, economic, and political factors that create disparities in hazard impacts and responses. Vulnerability is also affected by risk perceptions, which can influence protective behaviors. In this study, we use national survey data to investigate the association of key sociodemographic factors with public risk perceptions of heat waves. We find that risk perceptions are most associated with income, race/ethnicity, gender, and disability status. Age, an important predictor of heat mortality, had smaller associations with heat risk perceptions. Low-income, non-white, and disabled individuals tend to perceive themselves to be at greater risks from heat waves than other subpopulations, corresponding with their elevated risk. Men have lower risk perceptions than women despite their higher mortality and morbidity from heat. This study helps to identify subpopulations in the U.S. who see themselves as at risk from extreme heat and can inform heat risk communication and other risk reduction practices.

1. INTRODUCTION

Extreme heat events are one of the deadliest natural hazards in the United States (Berko et al. 2014; Gasparrini et al. 2015; U.S. EPA and CDC 2016) and pose deadly threats to people worldwide (Mora et al. 2017; Franzke and Torelló i Sentelles 2020). Extreme heat is projected to increase in frequency and severity in response to increasing atmospheric concentrations of greenhouse gases driven by human activity (Jeon et al. 2016; U.S. EPA and CDC 2016; Angélil et al. 2017; Vose et al. 2017; IPCC 2021). Urbanization is also increasing the number of people exposed to deadly heat waves (Tuholske et al. 2021). Furthermore, there is demonstrated influence of human activity on the severity of heat-health impacts (Vicedo-Cabrera et al. 2021), and individual behavior and risk judgements can lead to different impacts across similarly exposed populations (Semenza et al. 2008; White-Newsome et al. 2011; Lefevre et al. 2015;

Wilhelmi and Hayden 2010). Increasing physical exposure to extreme heat and its complex interaction with social sensitivity factors associated with social inequities in hazard impacts and responses (such as gender, age, and race/ethnicity) create varying risk environments for different subpopulations across the country. This underscores the need for decision-makers and risk managers to develop strategies and define priorities to mitigate the negative impacts of extreme heat, since heat mortality and morbidity are often preventable if appropriate individual and collective actions are taken.

In this study, we examine how sociodemographic indicators associated with health disparities in the impacts of extreme heat also influence risk perceptions across the contiguous United States. Using georeferenced survey data and multilevel regression modeling, we report the associations of individual-level factors (*e.g.* gender, age, race/ethnicity, work status) with risk perceptions, while also estimating risk perceptions among different subpopulations. These results provide decision makers with valuable information about which vulnerable subpopulation tends to perceive (or not) the threat of extreme heat which informs targeted risk communication and hazard preparedness campaigns.

2. LITERATURE REVIEW

2.1 Extreme heat risk

While there is no universal definition of an extreme heat event or heat wave, these events are commonly understood as periods characterized by excessively high levels of temperature and/or humidity that jeopardize human health due to severity of exposure or duration (Robinson 2001; Smith et al. 2013; White-Newsome et al. 2014; U.S. EPA and CDC 2016; Hawkins et al. 2017; Liss et al. 2017). Mora and colleagues (Mora et al. 2017) found that about 30% of the global population is exposed to deadly heat conditions for at least 20 days each year, and this number is expected to increase to between 48–74% by 2100 under different global warming scenarios. As temperatures continue to rise, a greater proportion of U.S. citizens will be exposed to extreme heat conditions in the future (Jones et al. 2015).

Extreme heat is a commonly experienced hazard with both immediate and delayed negative health impacts that can result in illness and fatalities during pronounced heat waves. For example, in July 1995, during a five-day extreme heat event in Chicago, Illinois, over 700 deaths were recorded in excess of historical norms, representing an increase of 85% from the previous year (Semenza et al. 1996; Klinenberg 2003). In May 2015, record temperatures throughout southern India led to at least 2,320 confirmed fatalities (Ratnam et al. 2016; Mazdiyasni et al. 2017). And in August 2003, a particularly severe heat wave affected much of western Europe claiming more than 70,000 lives (Robine et al. 2008). Despite these high numbers, heat deaths are likely underreported due to heat's tendency to exacerbate existing medical conditions (Åström et al. 2011; Liss et al. 2017; Mora et al. 2017). Some negative heat-health impacts such as dizziness and fatigue are experienced by a broader segment of the population (Khare et al. 2015; Hayden et al. 2017). For example, a study in England found that more than half of the younger adults reported experiencing headache and sunburn during summer 2013 (Khare et al. 2015). The intensity and scope of these impacts are influenced by geographic factors, population dynamics, time, scale, and the efficacy of communities' adaptive policies (Semenza et al. 1996; Klinenberg 2003; U.S. EPA 2006; Anderson and Bell 2011; Reid et al. 2012; IPCC 2014; Tierney 2014).

2.2. Risk assessment and extreme heat

Assessment of vulnerability and risk is critical to identify priorities and develop management strategies (IPCC 2012). Decision makers need locally relevant information about the distribution of potential negative impacts to inform mitigation and risk reduction strategies. The risks associated with climate change and natural hazards can be assessed by supplementing physical models of hazard exposure (Gill and Malamud 2014; Hawkins et al. 2017; Mora et al. 2017) with analyses that seek to incorporate dynamic human vulnerability factors that affect sensitivity and adaptive capacity (Reid et al. 2009; Tomlinson et al. 2011; Buscail et al. 2012; Wolf and McGregor 2013; Weber et al. 2015). Vulnerability is a key determinant of potential impacts of hazardous events, and sensitivity and lack of adaptive capacities are in turn causes of vulnerability (IPCC 2012). Sensitivity refers to the potential of being negatively affected by hazards due to personal, household, and contextual factors (such as social, economic, political, or cultural factors) that magnify the impact of a hazard event (Grothmann and Reusswig 2006; Johnson et al. 2012; Reid et al. 2012; IPCC 2014; Tierney 2014; Jones et al. 2015). Adaptive capacity is the ability of individuals or a group to take actions that mitigate hazard risks such as social capital (Kalkstein and Sheridan 2007; Bobb et al. 2014; IPCC 2014; Tierney 2014; Jones et al. 2015). While the ability to predict climatic changes and the occurrence of heat events on a global scale by better understanding the dynamic properties and interactions of the earth's natural systems has improved (Schellnhuber 1999; Famiglietti et al. 2015), the dynamic properties of human systems remain difficult to capture in comprehensive risk assessments.

In the context of extreme heat, some sociodemographic factors (see Table I) have been associated with disparities in morbidity and mortality from extreme heat and included in risk assessments as indicators of heat vulnerability (Harlan et al. 2006, 2013; Medina-Ramón et al. 2006; Anderson and Bell 2009, 2011; Reid et al. 2009, 2012; Buscail et al. 2012; Johnson et al.

2012; Wolf and McGregor 2013; Gronlund et al. 2014; Weber et al. 2015). Age is a demographic factor of heat vulnerability because older individuals are statistically more likely to be negatively impacted by extreme heat exposure as they tend to be more physiologically susceptible to heat, more limited in their ability to access health services due to mobility constraints, and more prone to social isolation (Semenza et al. 1996; Stafoggia et al. 2006; Reid et al. 2009; Uejio et al. 2011; Wolf and McGregor 2013; Gronlund et al. 2014; Liss et al. 2017). In the United States, epidemiological studies have found that men have higher rates of heat-related mortality and morbidity than women during extreme heat events (Semenza et al. 1996; Whitman et al. 1997; Choudhary and Vaidyanathan 2014; Hess et al. 2014; Schmeltz et al. 2015). Being active in the heat and lower social contact may contribute to higher heat vulnerability among men, although women face socioeconomic inequities in the United States that may also increase risk (Kovats and Hajat 2008). People with lower educational attainment tend to face greater natural hazard risks in general due to difficulties they face in accessing health services and hazard information (Cutter et al. 2003; Reid et al. 2009; Anderson and Bell 2011; Weber et al. 2015). Low-income and socioeconomically disadvantaged people, particularly disabled individuals, are significantly more likely to be negatively affected by natural hazards, including extreme heat, due to a lack of resources required to cope with the hazard (Harlan et al. 2006; Anderson and Bell 2009; Reid et al. 2009). Previous studies have indicated that larger households (with a greater number of residents) tend to have greater access to the social and material resources required to cope with heat hazards (but are more likely to have children more susceptible to negative heat impacts) whereas smaller households are more prone to social isolation, a significant source of vulnerability (Semenza et al. 1996; Cutter et al. 2003; Klinenberg 2003, 80–81; Reid et al. 2009; Weber et al. 2015). Due to social, political, and economic inequities, minoritized racial and ethnic populations often experience greater health impacts from extreme heat (Cutter et al. 2003; Reid et al. 2009; Anderson and Bell 2011; Weber et al. 2015), and can also be more exposed to extreme heat at the neighborhood level due to historic patterns of discrimination such as redlining (Benz and Burney 2021). These social, economic, and demographic factors can be categorized as "sensitivity" factors, but they may also influence adaptive capacity in shaping overall vulnerability.

2.3. Risk perception

In addition to these sensitivity factors, risk perception has also been acknowledged as an important factor of heat vulnerability (Wilhelmi and Hayden 2010). Risk perception is a determinant of individual risk decision-making and influences the likelihood of an individual engaging in personal protective behaviors (Slovic 1987; van der Pligt 1996; Brewer et al. 2004). Personal behavior and preparedness can either attenuate or exacerbate vulnerability. The relationship between risk perception and behavior has been studied with respect to certain environmental and health hazards (Wachinger et al. 2013). Previous studies have found that heat risk perceptions positively influence heat-protective behaviors (Lane et al. 2014; Hayden et al. 2017; Madrigano et al. 2018; Ban et al. 2019; Hass and Ellis 2019; Zander et al. 2019; Hass et al. 2021). For example, a recent U.S. national survey found that risk perceptions and subjective experience with health effects of extreme heat predicted heat-protective behaviors (Esplin et al. 2019). Data on risk perceptions provide information on how individuals perceive their own vulnerability and their likelihood of taking protective action (Tierney 2014), which are increasingly sought by government officials and risk managers (Wolf et al. 2010; Reid et al. 2012; White-Newsome et al. 2014).

While sociodemographic sensitivity factors such as age and housing characteristics can be included in risk assessment due to the availability of census data at sub-national levels, risk assessment typically lacks data on risk perception (Wilhelmi and Hayden 2010). Furthermore, little is known about what data may be good proxies for heat risk perception due to a lack of knowledge about how key sensitivity factors are associated with risk perception. Existing knowledge is limited to surveys in a small number of cities (Kalkstein and Sheridan 2007; Madrigano et al. 2018; Chakalian et al. 2019). For example, a study conducted in New York City found that low-income individuals were more likely to be concerned about heat, but men—who also have elevated vulnerability to heat—tended to have lower heat risk perceptions (Madrigano et al. 2018).

Risk reduction strategies may be more effective if they account for individual-level social factors related to hazard awareness, risk judgements, and subsequent decision-making behaviors that likely vary at sub-national levels (Slovic 1987; Renn 1998; Howe et al. 2019). Failure to account for risk perception in risk assessment can lead to inadequate hazard communication and misguided management priorities. For example, a lack of knowledge about the association of sensitivity factors and risk perception may result in difficulties in identifying communication priorities since little is known whether vulnerable populations perceive their elevated vulnerability. If a certain vulnerable subgroup does not perceive a higher risk of extreme heat events for themselves, their family, and their community, the subgroup should be a priority for practitioners to target risk communication efforts.

To bridge the knowledge gap, this study investigates how sociodemographic factors are associated with heat risk perception, using nationally representative survey data from the contiguous U.S. This study asks: how do key social, economic, and demographic factors known to be important indicators of mortality and morbidity from extreme heat (summarized in Table 1) relate to extreme heat risk perceptions? We hypothesize that individual-level factors that have been found to be associated with greater personal risk of heat-related impacts in previous studies will be positively associated with heat wave risk perceptions. This study complements Howe et al. (2019), which describes place-based geographic patterns in heat risk perceptions at multiple scales (census tract, county, and state) across the U.S. using small-area estimation models. Building on the same dataset, in this paper we focus on understanding how individual sociodemographic factors predict heat risk perceptions and how such factors interact with each other. By focusing on the predictors of heat risk perceptions, this research helps to identify particular subpopulations who face well-documented vulnerability but are less likely to perceive themselves to be at amplified risk from extreme heat. Such information can help decision makers to define communication priorities and assess hazard vulnerability and risk in a more comprehensive way.

3. METHODS

3.1. Study area and data

This study examines heat wave risk perceptions across the contiguous U.S. during the warm months of 2015 using nationally representative survey data (Supplementary Information, Fig. 1). The survey was administered online biweekly over the course of 20 weeks, beginning in May. The survey was conducted on the GfK KnowledgePanel Omnibus, a shared-cost weekly online survey whose respondents are sampled from a probability-based panel. GfK recruited panel members using address-based sampling of all U.S. addresses from the U.S. Postal Service Delivery Sequence File and provided households without internet access with a computer and internet service (in our sample, 20% of respondents lacked home broadband internet access). The overall sample size was n = 10,532. However, due to the panel design of this survey, responses were collected more than once for some individuals. These subsequent responses were filtered from the dataset before analysis and the final sample size was n = 8,789 unique respondents. Individual identifiers were removed from the data and the precise geographic coordinates of respondents were jittered within a radius of 150m for respondent confidentiality.

The survey was composed of three questions measuring heat wave risk perceptions on three sub-scales, measuring perceived risk to the individual respondent, their family, and their community:

> "A heat wave is a period of unusually and uncomfortably hot weather. If a heat wave were to occur in your local area, how much, if at all, do you think it would harm the following: Your health? Your family's health? The health of others in your community?"

The responses to each of the survey questions, which were collected using a slider bar on a 0-100 scale, were combined to create an overall heat wave risk perception index used as the dependent variable in this study. This index had high internal consistency (Cronbach's alpha = 0.95). The index represents heat wave risk perception values on a scale of 0–100 with 100 representing the highest degree of perceived risk to heat. The high internal consistency of the heat wave risk perception index suggests that it captures a single construct.

The survey also collected data on the sociodemographic characteristics of each respondent. Seven sociodemographic variables (gender, age, race/ethnicity, income, education, work status, household size) were used in this study's regression analyses along with geographic data recorded for each response. The structure of these variables is detailed in Supplementary Info, Table 1.

3.2. Analysis

The scope of this analysis is focused on evaluating the sociodemographic factors associated with risk perceptions, rather than developing an exhaustive model capturing all possible factors. We fit a random intercept (multilevel) regression model to the heat wave risk perception index, parameterized according to statistical best practices for confirmatory hypothesis testing (Hofmann 1997; Gelman and Hill 2007, chap. 11–12; Zuur et al. 2009; Barr et al. 2013). The purpose of the models in this paper is explanatory rather than predictive, and designed to test hypotheses about associations between known vulnerability factors and risk perceptions. The same methods and statistical techniques described below for the initial model build were applied to each subsequent model. All analyses were performed using the R programming language and environment using the lme4 package (Bates et al. 2015).

The initial model (Supplementary Table 2) was composed solely of categorical random effects (Winter; Hofmann 1997; Barr et al. 2013). The model coefficients (effects) associated with these predictors and their sublevels are random effects estimated with partial pooling—also known as linear unbiased prediction (Winter; Goldberger 1962; Gelman and Hill 2007, chap. 12). By treating the extreme heat risk factors addressed in the study hypotheses as random effects, the effect of the levels of each predictor can be assessed in relation to their difference from the overall mean (i.e., the average risk perception score across the U.S. population) (Robinson 1991; Hofmann 1997; Barr et al. 2013).

Multilevel regression models use best linear unbiased predictors (BLUPs) to predict random effect values rather than estimate fixed parameters and establish a hierarchical framework through which meaningful differences between levels can be discerned. The BLUPs are analogous to prediction in the Empirical Bayes methodological framework, in which parameters associated with a pre-specified prior distribution are estimated from the data, thereby approximating the full hierarchical Bayes model (Hofmann 1997; Gelman and Hill 2007, chap. 11; Barr et al. 2013). By utilizing prediction instead of estimation, the strengths of Bayesian inference can be integrated within a classical statistical framework to support hierarchical linear modeling. Consequently, we employ BLUPs because the primary interest of this study is in making inferences about the distribution of risk perception values, their degree of variance at different levels, and the underlying population more so than in the effects themselves (e.g. fixed effects) or explicitly testing for measurable differences between specific levels (Gelman and Hill 2007, chap. 11).

The following equation shows our initial model specification using variables identified in previous literature related to heat sensitivity:

$$Y_{m_i,\ldots,v_i} = \mu + \alpha_m^{age} + \alpha_n^{gender} + \alpha_o^{race/ethnicity} + \alpha_p^{race/ethnicity:gender} + \alpha_q^{income}$$

$$+ \alpha_r^{education} + \alpha_s^{work} + \alpha_t^{hhsize} + \alpha_u^{state} + \alpha_v^{region} + \varepsilon_i, \text{for } i = 1, \ldots 8789$$

where…

$$\alpha_m^{age} \sim N(0, \sigma_{age}^2), \text{for } m = 1, \ldots, 5$$

$$\alpha_n^{gender} \sim N(0, \sigma_{gender}^2), \text{for } n = 1,2$$

$$\alpha_o^{race/ethnicity} \sim N(0, \sigma_{race/ethnicity}^2), \text{for } o = 1, \ldots, 5$$

$$\alpha_p^{race/ethnicity:gender} \sim N(0, \sigma_{race/ethnicity:gender}^2), \text{for } p = 1, \ldots, 10$$

$$\alpha_q^{income} \sim N(0, \sigma^2_{income}), \text{for } q = 1, \dots, 7$$

$$\alpha_r^{education} \sim N(0, \sigma^2_{education}), \text{for } r = 1, \dots, 4$$

$$\alpha_s^{work} \sim N(0, \sigma^2_{work}), \text{for } s = 1, \dots, 5$$

$$\alpha_t^{hhsize} \sim N(0, \sigma^2_{hhsize}), \text{for } t = 1, \dots, 4$$

$$\alpha_u^{state} \sim N(0, \sigma^2_{state}), \text{for } u = 1, \dots, 51$$

$$\alpha_v^{region} \sim N\left(0, \sigma^2_{region}\right), \text{for } v = 1, \dots, 4$$

Predictors were included or dropped from the model based on tests of model fit. Model fit was assessed using chi-square tests on the log-likelihood values through iterative ANOVA testing to compare models reduced by one variable (subject to the ANOVA testing) and determine that variable's contribution to the overall model fit via reduction in the residual sum of squares (Barr et al. 2013; Bates et al. 2015). The contribution of each predictor to variance in risk perceptions was tested by comparing the null (full Sensitivity Model) to a series of models each missing one random effect term (Supplementary Table 2).

In a mixed effect model, inter-correlations between fixed effects can quickly be assessed en masse via a correlation matrix; however, random effect models require systematic evaluation of each predictor's individual contribution to the model. Multilevel modeling best practices (Hofmann 1997; Gelman and Hill 2007) involve starting with a maximal model and using log-likelihood tests to iteratively pare down the number of predictors. Best practices also indicate that in many circumstances, it is more appropriate to retain predictors that would otherwise be eliminated after the log-likelihood test because they are important to the conceptual or theoretical framework adopted across the study -- for example, including or excluding the theoretically important random effect "Education" had no quantifiable impact on model output (Table II).

Our model specification includes the following sociodemographic predictors: gender, age, race/ethnicity, income, education, work status, and household size. Descriptive statistics are available in Supplementary Table 1. In addition to these sociodemographic variables, we also include an interaction term for gender by race and ethnicity, since this interaction is supported by previous research on hazard risk perceptions: the "white male effect" found in many risk perception studies (that white males tend to exhibit lower risk perceptions than other demographic groups) indicates that the interaction of gender and race/ethnicity is important to include in models of risk perceptions, since the effects of gender and race/ethnicity alone do not fully capture the effect (Finucane et al. 2000). In addition, by using random effects associated with geographic factors (Census region, state), the model was able to account for some degree of spatial autocorrelation and overcome assumptions of independence that would normally be violated if geographically clustered data were to be analyzed using traditional linear regression modeling (Hofmann 1997; Gelman and Hill 2007, chap. 11).

Model results describe inter-group variation across sociodemographic factors hypothesized to influence heat wave risk perceptions. The outcome variable is a risk perception index on a scale of 0–100 with 100 representing the highest degree of perceived risk. Random effects included in this model provide a direct measure of how much of the reported risk perception scores' variance around this mean is explained by group-level differences.

4. RESULTS

Nationwide, the mean heat wave risk perception index was 39 (n = 8789, *sd* = 24) on a 0-100 scale (Supplementary Fig. 2). Heat wave risk perception was associated with the following statistically significant predictors: race/ethnicity, income, gender, work status, age, state and region (Table 2).

Income was a statistically significant predictor of individual heat wave risk perceptions with a large effect size ($\sigma = 3.72$, $X^2(1) = 89.52$, $p < 0.001$). Higher-income individuals tend to have lower risk perceptions than lower-income individuals (Fig. 1) and the national average. Holding other predictors constant at their means, respondents earning less than $15,000 per year scored 1.26 times higher on the heat wave risk perception index (47) than respondents earning over $150,000 per year (37).

Race and ethnicity was also a strong and significant predictor of heat wave risk perceptions ($\sigma = 3.51$, X^2 $(2) = 103.98$, $p < 0.001$). Holding other variables constant, white, non-Hispanic or Latino respondents had the lowest estimated heat wave risk perception index at 37, while Hispanic or Latino (44) and Other, non-Hispanic or Latino respondents (47) had the highest estimated heat wave risk perception index (this category includes non-Hispanic or Latino Asian, American Indian or Alaska Native, and Native Hawaiian or other Pacific Islander U.S. residents). Gender was a statistically significant predictor of heat wave risk perceptions ($\sigma = 2.32$, X^2 $(2) = 80.27$, $p < 0.001$). Although the effect was not large, the heat wave risk perception index was higher among women (44) than men (41). While the race/ethnicity by gender interaction did not significantly improve model fit overall ($\sigma = 0.95$, X^2 $(2) = 1.84$, $p = 0.17$), white non-Hispanic or Latino male respondents tended to have much lower heat wave risk perceptions scores (35) than the mean for all other race by gender groupings (43).

Work status was also a strong and statistically significant predictor of heat wave risk perceptions ($\sigma = 2.99$, $X^2(1) = 29.77$, $p < 0.001$). Across five work status categories, disabled non-working respondents reported much higher heat wave risk perceptions (48) than those in the remaining four work status categories (not working – seeking a job, 42; working, 41; not working – retired, 41; not working – other, 40).

Age was a small but significant predictor of heat wave risk perceptions ($\sigma = 1.08$, X^2 (1) = 6.17, $p = 0.0129$). Respondents in the older age categories (65 years and older and 45-54 years) had slightly higher heat wave risk perceptions (44) than those in the 35-44 year old category (41).

The remaining sociodemographic variables did not significantly improve model fit. Heat wave risk perceptions did not show significant variation by educational attainment ($\sigma = 0.37$, X^2 (1) = 0.09, $p = 0.76$) or household size ($\sigma = 0.58$, X^2 (1) = 1.35, $p = 0.25$).

We estimated variation in the heat wave risk perception index was across geographic units (state and region) using the same techniques, by specifying geographic units as random effects. Respondents' state of residence was a statistically significant predictor of heat wave risk perceptions ($\sigma = 2.25$, X^2 (1) = 24.94, $p < 0.001$). At a broader scale, the US Census region in which each state was grouped was also a statistically significant predictor of risk perceptions and explained variation beyond that at the state level ($\sigma = 2.23$, (1) = 10.62, $p = 0.001$). The Midwest tended to have the lowest heat wave risk perceptions (39.9) while the South had the highest risk perceptions (44.9). Geographic effects are summarized in Supplementary Fig. 3. Howe et al.(Howe et al. 2019) provides additional detail on geographic variation in heat risk perceptions at multiple scales.

5. DISCUSSION

The principal objective of this study was to determine how key sociodemographic factors known to be important contributors to overall heat vulnerability (summarized in Table I) also influence heat wave risk perceptions across the contiguous U.S. Several individual-level sociodemographic factors were associated with differences in heat wave risk perceptions—either positively or negatively, as hypothesized—and accounted for a statistically significant proportion of total variance around the national average. Overall, sociodemographic predictors explain a similar amount of individual variation in heat wave risk perceptions as they do risk perceptions to other hazards (Peacock et al. 2005; Lindell and Hwang 2008; Kellens et al. 2011; Knuth et al. 2013).

This study also has several limitations. While our findings are based on a nationally representative survey sample and generalizable to the U.S. population, low-population sociodemographic groups are less represented in our sample, which limits the ability to draw conclusions about their heat risk perceptions. Our survey data were collected during one season (Summer 2015), which may limit our ability to generalize to other seasons where heat is a potential hazard (such as late spring or early fall) or other years in which the U.S. population may experience different patterns of weather conditions. A third limitation is that we focus here only on several survey questions risk perceptions of heat. Resource constraints limited our ability to collect additional survey questions which may provide a fuller picture of impacts, decision-making, and responses to heat among the American public (e.g. Esplin et al. 2019). For example, future surveys should examine how experiences with direct and indirect heat-health impacts may influence risk perceptions.

Heat wave risk perception indices for subpopulations known to be at increased risk tended to deviate from the national average in line with the directionality of their effect on heat vulnerability, as found by previous research, with the notable exception of gender. Gender, a factor which previous studies have identified as an important determinant of extreme heat sensitivity, is an important determinant of risk perception. However, men—who experience more impacts from heat to their health (Semenza et al. 1996; Whitman et al. 1997; Kovats and Hajat 2008; Choudhary and Vaidyanathan 2014; Hess et al. 2014; Schmeltz et al. 2015)—perceive themselves to be at lower risk than women. This finding suggests particular importance for risk communicators to conduct targeted communication efforts to men in the United States. Minoritized racial groups are known to be at increased risk of being negatively impacted by extreme heat (Cutter et al. 2003; Klinenberg 2003, 80–81; Anderson and Bell 2009, 2011; Reid et al. 2009, 2012; Wolf and McGregor 2013; Weber et al. 2015) and also tend to have higher heat risk perceptions. Previous studies have found that working, non-disabled individuals are less sensitive to negative hazard impacts, while disabled persons are more susceptible to negative impacts (Semenza et al. 1996; Cutter et al. 2003; Klinenberg 2003, 80–81; U.S. EPA 2006; IPCC 2014; Ebi et al. 2018; U.S. EPA and CDC 2016). In this study, disabled non-working respondents reported much higher heat wave risk perceptions. As hypothesized, respondents with higher incomes tended to have much lower heat risk perceptions than the national average, individuals with lower incomes tended to have higher risk perceptions.

The relatively low variance across some subpopulations may be partially a consequence of the conservative nature of mixed effect models, which rely upon partial pooling and combinations of individual-level and contextual-level characteristics that tend to pull subpopulation estimates toward their respective national averages. Despite this, a few at-risk subpopulations tended to have lower risk perceptions than expected (Fig. 1). Some factors known to increase vulnerability, such as age and education, were not associated with substantial differences in risk perception. Although age—a factor which previous studies have identified as an important determinant of extreme heat health impacts (Klinenberg 2003; Anderson and Bell 2009, 2011; White-Newsome et al. 2014; Gronlund et al. 2014)—was found to be a statistically significant predictor of heat risk perceptions, practically it did not have a pronounced effect on extreme heat risk perception. The most senior subpopulation (≥ 65 years of age) reported only slightly higher risk perceptions than younger subpopulations despite their elevated risk. While we cannot identify whether this pattern is due to younger subpopulations overestimating their risk or older subpopulations underestimating their risk, we would still expect to find larger differences between the two groups if risk perceptions aligned with health risks. Since they do not, the possible underestimation of extreme heat risk by a particularly vulnerable subpopulation indicates that older populations may be less likely to take protective behaviors than would be appropriate given their risk profile. This is particularly significant given that an aging, increasingly urban U.S. population—with an increasing number of individuals considered to be vulnerable to heat (Basu 2009; Ortman et al. 2014; Jones et al. 2015; Lehner and Stocker 2015; Mora et al. 2017) —will likely be exposed to more frequent and intense extreme heat events – particularly in urban heat islands (Tomlinson et al. 2011; Li and Bou-Zeid 2013; U.S. EPA and CDC 2016). This increasing exposure, combined with a tendency to underestimate age-related risk, suggests that risk-reduction programs should also be focused on older individuals, including risk communication efforts.

No relationship was observed between education and heat risk perception despite the fact that individuals with lower educational attainment often face greater difficulty in accessing health services and information regarding the nature of natural hazards (Cutter et al. 2003;

Medina-Ramón et al. 2006; U.S. EPA 2006; Anderson and Bell 2009, 2011; Reid et al. 2009, 2012; Smith 2013, 85–86; Weber et al. 2015; U.S. EPA and CDC 2016).

Additionally, previous research has identified household size as an important predictor of hazard risk, as larger households with more people living together are more likely to have the financial and social resources required to cope with environmental hazards and avoid social isolation (Semenza et al. 1996; Cutter et al. 2003; Klinenberg 2003, 80–81; Reid et al. 2009, 2012; Weber et al. 2015). In our model household size had no effect on heat wave risk perception when also controlling for income.

Overall, we find evidence that the socioeconomic factors associated with health impacts from extreme heat correspond in many ways to the factors associated with heat risk perceptions among the U.S. population. Income tends to be a strong predictor of heat risk perceptions, along with work status, gender, and race/ethnicity. Conceptually, income is directly associated with the ability to protect oneself from the heat through, for example, household adaptations such as installing and using air conditioning. Income is also associated with employment type and location. While our survey did not include detailed questions on employment type, higher-paying occupations tend to be located in indoor climate-controlled environments, while many outdoor occupations are lower paying (such as agricultural and construction labor) and employees in such outdoor occupations are exposed to greater heat risks.

The results of this study and Howe et al. (2019) show that heat wave perceptions do vary spatially and demonstrate statistically significant, non-random geographic patterns. People living in regions with histories of greater exposure to extreme heat events tended to have higher risk perceptions (Howe et al. 2019). However, this study indicates that the association of key sociodemographic variables with heat wave risk perceptions persists even after controlling for geography. In addition, our individual-level analysis identifies patterns less clearly visible at the state, community, or neighborhood level. For example, Howe et al. (2019) show that counties with older populations do not, on average, have higher heat risk perceptions than counties with younger populations. Our results, however, show a small but statistically significant positive relationship between age and heat risk perceptions across the population. Furthermore, we demonstrate the meaningful effects of certain key individual predictors (such as gender and work status) that may themselves vary less across communities but more between and within households, and remain important factors for understanding how people perceive risks.

Taken together, heat wave risk perceptions demonstrate substantial variation across the U.S. population. For example, the combination of race and ethnicity with income illustrates a wide range of predicted heat wave risk perceptions (Fig. 2). Selected sociodemographic factors including income, race/ethnicity, work status, and gender exhibit similar or greater variance to the broad-scale geographic factors of state and region. When combined, demographic and geographic factors are associated with large variation in risk perceptions across the population. Across all possible combinations, we estimate that the group with the highest heat wave risk perceptions (65.1) are Louisiana women 45-54 years old in the "other, non-Hispanic or Latino" race/ethnicity category (which includes Asian, American Indian or Alaska Native, Native Hawaiian or other Pacific Islander U.S. residents) who are disabled and not working with incomes of less than $15,000 per year. By contrast, the group estimated to have the lowest heat wave risk perceptions (22.0) are Minnesota men 35-44 years old in the "white, non-Hispanic or Latino" race/ethnicity category who are not disabled with incomes of greater than $150,000 per year.

Findings of this study inform risk communication strategies and risk reduction management in two ways. First, for men and older adults, our study suggests that these groups tend to underestimate their elevated vulnerability from extreme heat (although we cannot rule out the possibility that comparison groups are relatively overestimating their vulnerability). The underestimation of risks is likely to contribute to maladaptation during extreme heat events (Esplin et al. 2019; Hass and Ellis 2019). This finding highlights the importance to conduct targeted risk communication and help people in the United States to fully understand their risks. Compared to efficacy statements (e.g., information about the location of cooling centers), communication strategies that emphasize vulnerability (e.g., explanations about why all people are vulnerable to extreme heat) should be prioritized to test in future studies to better communicate heat-health risks (e.g. Li et al. 2021). Second, for low-income, non-white, and disabled subpopulations, this study found that these subpopulations have much higher heat risk perceptions than the national average, which is in line with their elevated risk of health impacts from heat. For risk management and communication with these subpopulations, this finding suggests that it is important to allocate resources (such as utility bill relief) to help at-risk populations cope with extreme heat. When communicating with such populations, efficacy statements about how to reduce their risks—compared to strategies emphasizing vulnerability—might be more effective to help them overcome barriers to taking protective actions.

6. CONCLUSIONS

Using national survey data, we used hierarchical linear models to examine how sociodemographic and geographic variables relate to heat wave risk perception in the U.S. The direction of heat wave risk perception predictors across the contiguous U.S. generally reflects trends identified in health impacts for many sociodemographic factors, with the notable exceptions of gender and, to some extent, age. Highlighting the distribution of perceived risk can help set priorities for subpopulation-specific risk communication strategies. Our results allow estimates of risk perceptions for specific subpopulations in relation to overall national trends. Variation in specific subpopulations, especially at the extremes, may be of particular interest for risk reduction efforts, including targeted risk communication.

Low risk perception increases vulnerability because people are less likely to respond to the hazards they do not perceive. In other words, what we believe to be real shapes our behavior—reactively or proactively. When vulnerable subpopulations, such as men and the elderly, do not perceive themselves to be at greater risk from heat, this presents barriers to risk reduction. This study found that age did not substantively influence heat risk perception, suggesting that older people may underestimate their elevated risk. In addition, men may also underestimate their increased risk from extreme heat events. These findings can inform risk communication programs to target these populations who may not currently fully understand their vulnerability. Effective risk communication strategies can reduce sensitivity to heat and enhance adaptive capacity by promoting protective behavior at the individual and community-level. For example, the protective behaviors promoted by risk communication campaigns might include risk awareness, avoiding unnecessary exposure, developing personal heat-safety plans. The first steps in designing effective risk communication programs are identifying vulnerable subpopulations, studying their distribution, and evaluating their unique circumstances; data on risk perception and its association with sociodemographic factors help accomplish these goals.

Heat risk is increasing around the world due to global warming caused by anthropogenic greenhouse gas emissions and urbanization, but total hazard risk can be reduced by targeted interventions aimed at strengthening adaptive capacity and addressing human vulnerability factors (Adger 2006; Smit and Wandel 2006; Noble et al. 2014, 847–849). To do this, researchers, risk managers, and community members will need to work together to identify vulnerability factors (Mimura et al. 2014, 871–877; Ebi et al. 2018). This study details a new systematic approach for understanding risk perceptions across subpopulations using nationally representative survey data that is generalizable to the U.S. population. Leveraging advances in both the natural and social sciences to understand the drivers and distribution of heat vulnerability is vital to minimizing future loss in the face of rising exposure. Studying the landscapes of beliefs, risk perceptions, and behaviors can inform policy as well as our understanding of vulnerability at a range of temporal and spatial scales.

ACKNOWLEDGEMENTS

This work was partially supported by the National Science Foundation (SES-1459903, SES-1459872, & BCS-1753082). Thanks to E. Helen Berry, Claudia Radel, and Beth Shirley for comments and suggestions.

DATA AVAILABILITY STATEMENT

Data that support the findings of the paper will be deposited in the Digital Commons at Utah State University when the paper is published.

REFERENCES

Adger, W. N., 2006: Vulnerability. *Global Environmental Change*, **16**, 268–281, https://doi.org/10.1016/j.gloenvcha.2006.02.006.

Anderson, B. G., and M. L. Bell, 2009: Weather-Related Mortality: How Heat, Cold, and Heat Waves Affect Mortality in the United States. *Epidemiology*, **20**, 205–213, https://doi.org/10.1097/EDE.0b013e318190ee08.

——, and ——, 2011: Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. *Environmental Health Perspectives*, **119**, 210—218, https://doi.org/10.1289/ehp.1002313.

Angélil, O., D. Stone, M. Wehner, C. J. Paciorek, H. Krishnan, and W. Collins, 2017: An independent assessment of anthropogenic attribution statements for recent extreme temperature and rainfall events. *Journal of Climate*, **30**, 5–16, https://doi.org/10.1175/JCLI-D-16-0077.1.

Åström, D. O., F. Bertil, and R. Joacim, 2011: Heat wave impact on morbidity and mortality in the elderly population: A review of recent studies. *Maturitas*, **69**, 99–105, https://doi.org/10.1016/j.maturitas.2011.03.008.

Ban, J., W. Shi, L. Cui, X. Liu, C. Jiang, L. Han, R. Wang, and T. Li, 2019: Health-risk perception and its mediating effect on protective behavioral adaptation to heat waves. *Environmental Research*, **172**, 27–33, https://doi.org/https://doi.org/10.1016/j.envres.2019.01.006.

Barr, D. J., L. Roger, C. Scheepers, and H. J. Tily, 2013: Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*, **68**, 255–278, https://doi.org/10.1016/j.jml.2012.11.001.

Basu, R., 2009: High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. *Environmental Health*, **8**, https://doi.org/10.1186/1476-069X-8-40.

Bates, D., M. Mächler, B. Bolker, and S. Walker, 2015: Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, **67**, 1–48, https://doi.org/10.18637/jss.v067.i01.

Benz, S. A., & Burney, J. A. (2021). Widespread Race and Class Disparities in Surface Urban Heat Extremes Across the United States. *Earth's Future*, *9*(7), e2021EF002016. https://doi.org/10.1029/2021EF002016

Berko, J., D. D. Ingram, S. Saha, and J. D. Parker, 2014: Deaths Attributed to Heat, Cold, and Other Weather Events in the United States, 2006-2010. *National health statistics reports*, 1–15.

Bobb, J. F., R. D. Peng, M. L. Bell, and F. Dominici, 2014: Heat-Related Mortality and Adaptation to Heat in the United States. *Environmental Health Perspectives*, **122**, 811–816, https://doi.org/10.1289/ehp.1307392.

Brewer, N. T., N. D. Weinstein, C. L. Cuite, and J. E. Herrington, 2004: Risk perceptions and their relation to risk behavior. *Annals of Behavioral Medicine*, **27**, 125–130, https://doi.org/10.1207/s15324796abm2702_7.

Buscail, C., E. Upegui, and J.-F. Viel, 2012: Mapping heatwave health risk at the community level for public health action. *International Journal of Health Geographics*, **11**, 38, https://doi.org/10.1186/1476-072X-11-38.

Chakalian, P. M., L. Kurtz, S. L. Harlan, D. White, C. J. Gronlund, and D. M. Hondula, 2019: Exploring the Social, Psychological, and Behavioral Mechanisms of Heat Vulnerability in the City of Phoenix, AZ. *Journal of Extreme Events*, **06**, 2050006, https://doi.org/10.1142/S2345737620500062.

Choudhary, E., and A. Vaidyanathan, 2014: Heat stress illness hospitalizations--environmental public health tracking program, 20 States, 2001-2010. *Morbidity and mortality weekly report. Surveillance summaries (Washington, D.C. : 2002)*, **63**, 1—10.

Curriero, F. C., K. S. Heiner, J. M. Samet, S. L. Zeger, L. Strug, and J. A. Patz, 2002: Temperature and Mortality in 11 Cities of the Eastern United States. *American Journal of Epidemiology*, **155**, 80–87, https://doi.org/10.1093/aje/155.1.80.

Cutter, S. L., B. J. Boruff, and W. L. Shirley, 2003: Social Vulnerability to Environmental Hazards. *Social Science Quarterly*, **84**, 242–261, https://doi.org/10.1111/1540-6237.8402002.

Ebi, K. L., Balbus, J. M., Luber, G., Bole, A., Crimmins, A., Glass, G., Saha, S., Shimamoto, M. M., Trtanj, J., & White-Newsome, J. L. (2018). Human Health. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* (pp. 1–470). U.S. Global Change Research Program, Washington, DC. https://nca2018.globalchange.govhttps://nca2018.globalchange.gov/chapter/14

Esplin, E. D., J. R. Marlon, A. Leiserowitz, and P. D. Howe, 2019: “Can you take the heat?” Heat-induced health symptoms are associated with protective behaviors. *Weather, Climate, and Society*, **11**, 401–417.

Famiglietti, J. S., A. Cazenave, A. Eicker, J. T. Reager, M. Rodell, and I. Velicogna, 2015: Satellites provide the big picture. *Science*, **349**, 684–685.

Finucane, M. L., P. Slovic, C. K. Mertz, J. Flynn, and T. A. Satterfield, 2000: Gender, race, and perceived risk: The “white male” effect. *Health, Risk & Society*, **2**, 159–172.

Franzke, C. L. E., and H. Torelló i Sentelles, 2020: Risk of extreme high fatalities due to weather and climate hazards and its connection to large-scale climate variability. *Climatic Change*, **162**, 507–525, https://doi.org/10.1007/s10584-020-02825-z.

Gasparrini, A., and Coauthors, 2015: Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet*, **386**, 369–375.

Gelman, A., and J. Hill, 2007: *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press, 648 pp.

Gill, J. C., and B. D. Malamud, 2014: Reviewing and visualizing the interactions of natural hazards. *Reviews of Geophysics*, **52**, 680–722, https://doi.org/10.1002/2013RG000445.

Goldberger, A. S., 1962: Best Linear Unbiased Prediction in the Generalized Linear Regression Model. *Journal of the American Statistical Association*, **57**, 369–375.

Gronlund, C. J., A. Zanobetti, J. D. Schwartz, G. A. Wellenius, M. S. O'Neill, and M. S. O'Neill, 2014: Heat, Heat Waves, and Hospital Admissions among the Elderly in the United States, 1992–2006. *Environmental Health Perspectives*, **122**, 1187–1192, https://doi.org/10.1289/ehp.1206132.

Grothmann, T., and F. Reusswig, 2006: People at Risk of Flooding: Why Some Residents Take Precautionary Action While Others Do Not. *Natural Hazards*, **38**, 101–120, https://doi.org/10.1007/s11069-005-8604-6.

Harlan, S. L., A. J. Brazel, L. Prashad, W. L. Stefanov, and L. Larsen, 2006: Neighborhood microclimates and vulnerability to heat stress. *Social Science & Medicine*, **63**, 2847–2863, https://doi.org/10.1016/j.socscimed.2006.07.030.

——, J. H. Declet-Barreto, W. L. Stefanov, and D. B. Petitti, 2013: Neighborhood Effects on Heat Deaths: Social and Environmental Predictors of Vulnerability in Maricopa County, Arizona. *Environmental Health Perspectives*, **121**, 197–204, https://doi.org/10.1289/ehp.1104625.

Hass, A. L., and K. N. Ellis, 2019: Using wearable sensors to assess how a heatwave affects individual heat exposure, perceptions, and adaption methods. *International Journal of Biometeorology*, **63**, 1585–1595, https://doi.org/10.1007/s00484-019-01770-6.

Hass, A. L., J. D. Runkle, and M. M. Sugg. 2021. The driving influences of human perception to extreme heat: A scoping review. *Environmental Research* 197:111173.

Hawkins, M. D., V. Brown, and J. Ferrell, 2017: Assessment of NOAA National Weather Service Methods to Warn for Extreme Heat Events. *Weather, Climate, and Society*, **9**, 5–13, https://doi.org/10.1175/WCAS-D-15-0037.1.

Hayden, M. H., and Coauthors, 2017: Adaptive Capacity to Extreme Heat: Results from a Household Survey in Houston, Texas. *Weather, Climate, and Society*, **9**, 787–799, https://doi.org/10.1175/WCAS-D-16-0125.1.

Hess, J. J., S. Saha, and G. Luber, 2014: Summertime acute heat illness in US Emergency Departments from 2006 through 2010: analysis of a nationally representative sample. *Environmental Health Perspectives (Online)*, **122**, 1209, https://doi.org/10.1289/ehp.1306796.

Hofmann, D. A., 1997: An overview of the logic and rationale of hierarchical linear models. *Journal of Management*, **23**, 723–744, https://doi.org/10.1016/S0149-2063(97)90026-X.

Howe, P. D., M. Mildenberger, J. R. Marlon, and A. Leiserowitz, 2015: Geographic variation in opinions on climate change at state and local scales in the USA. *Nature Climate Change*, **5**, 596–603, https://doi.org/10.1038/nclimate2583.

——, J. R. Marlon, X. Wang, and A. Leiserowitz, 2019: Public perceptions of the health risks of extreme heat across US states, counties, and neighborhoods. *Proceedings of the National Academy of Sciences*, **116**, 6743–6748, https://doi.org/10.1073/pnas.1813145116.

IPCC, 2012: *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. C.B. Field et al., Eds. Cambridge University Press, Cambridge, UK, and New York, NY, USA, 582 pp.

——, 2014: Summary for policymakers. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, C.B. Field et al., Eds., Cambridge University Press, 1–32.

——, 2021: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. V. Masson-Delmotte et al., Eds. Cambridge University Press, In Press.

Jeon, S., C. J. Paciorek, and M. F. Wehner, 2016: Quantile-based bias correction and uncertainty quantification of extreme event attribution statements. *Weather and Climate Extremes*, **12**, 24–32, https://doi.org/10.1016/j.wace.2016.02.001.

Johnson, D. P., J. S. Wilson, and G. C. Luber, 2009: Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *International Journal of Health Geographics*, **8**, 1–13, https://doi.org/10.1186/1476-072X-8-57.

Johnson, D. P., A. Stanforth, V. Lulla, and G. Luber, 2012: Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. *Applied Geography*, **35**, 23–31, https://doi.org/10.1016/j.apgeog.2012.04.006.

Jones, B., B. C. O'Neill, L. McDaniel, S. McGinnis, L. O. Mearns, and C. Tebaldi, 2015: Future population exposure to US heat extremes. *Nature Climate Change*, **5**, 652–655, https://doi.org/10.1038/nclimate2631.

Kalkstein, A. J., and S. C. Sheridan, 2007: The social impacts of the heat–health watch/warning system in Phoenix, Arizona: assessing the perceived risk and response of the public. *International Journal of Biometeorology*, **52**, 43–55, https://doi.org/10.1007/s00484-006-0073-4.

Kellens, W., R. Zaalberg, T. Neutens, W. Vanneuville, and P. De Maeyer, 2011: An Analysis of the Public Perception of Flood Risk on the Belgian Coast. *Risk Analysis*, **31**, 1055–1068.

Khare, S., S. Hajat, S. Kovats, C. E. Lefevre, W. B. de Bruin, S. Dessai, and A. Bone, 2015: Heat protection behaviour in the UK: results of an online survey after the 2013 heatwave. *BMC Public Health*, **15**, 878, https://doi.org/10.1186/s12889-015-2181-8.

Klinenberg, E., 2003: *Heat wave: A social autopsy of disaster in Chicago*. Chicago: University of Chicago Press, 1–320 pp.

Knuth, D., D. Kehl, L. Hulse, and S. Schmidt, 2013: Risk Perception, Experience, and Objective Risk: A Cross-National Study with European Emergency Survivors. *Risk Analysis*, **34**, 1286–1298, https://doi.org/10.1111/risa.12157.

Kovats, R. S., and S. Hajat, 2008: Heat Stress and Public Health: A Critical Review. *Annual Review of Public Health*, **29**, 41–55, https://doi.org/10.1146/annurev.publhealth.29.020907.090843.

Lane, K., K. Wheeler, K. Charles-Guzman, M. Ahmed, M. Blum, K. Gregory, N. Graber, N. Clark, and T. Matte. 2014. Extreme Heat Awareness and Protective Behaviors in New York City. *Journal of Urban Health* 91 (3):403–414.

Lefevre, C. E., W. B. de Bruin, A. L. Taylor, S. Dessai, S. Kovats, and B. Fischhoff, 2015: Heat protection behaviors and positive affect about heat during the 2013 heat wave in the United

Kingdom. *Social Science & Medicine*, **128**, 282–289, https://doi.org/10.1016/j.socscimed.2015.01.029.

Lehner, F., and T. F. Stocker, 2015: From local perception to global perspective. *Nature Climate Change*, **5**, 731–734.

Li, D., and E. Bou-Zeid, 2013: Synergistic Interactions between Urban Heat Islands and Heat Waves: The Impact in Cities Is Larger than the Sum of Its Parts. *Journal of Applied Meteorology and Climatology*, **52**, 2051–2064, https://doi.org/10.1175/JAMC-D-13-02.1.

Li, Y., Hughes, A. L., & Howe, P. D. (2021). Toward Win-win Message Strategies: The Effects of Persuasive Message Content on Retweet Counts During Natural Hazard Events. *Weather, Climate, and Society*, *13*(3), 487–502. https://doi.org/10.1175/WCAS-D-20-0039.1

Lindell, M. K., and S. N. Hwang, 2008: Households' Perceived Personal Risk and Responses in a Multihazard Environment. *Risk Analysis*, **28**, 539–556, https://doi.org/10.1111/j.1539-6924.2008.01032.x.

Liss, A., R. Wu, K. K. H. Chui, E. N. Naumova, Liss. Alexander, R. Wu, K. K. H. Chui, and E. N. Naumova, 2017: Heat-Related Hospitalizations in Older Adults: An Amplified Effect of the First Seasonal Heatwave. *Scientific Reports*, **7**, 39581, https://doi.org/10.1038/srep39581.

Madrigano, J., K. Lane, N. Petrovic, M. Ahmed, M. Blum, and T. Matte, 2018: Awareness, Risk Perception, and Protective Behaviors for Extreme Heat and Climate Change in New York City. *International journal of environmental research and public health*, **15**.

Mazdiyasni, O., and Coauthors, 2017: Increasing probability of mortality during Indian heat waves. *Science Advances*, **3**, e1700066, https://doi.org/10.1126/sciadv.1700066.

Medina-Ramón, M., A. Zanobetti, D. P. Cavanagh, and J. Schwartz, 2006: Extreme temperatures and mortality: assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. *Environmental health perspectives*, **114**, 1331–1336, https://doi.org/10.1289/ehp.9074.

Mimura, N., R. S. Pulwarty, I. Elshinnawy, M. H. Redsteer, H. Q. Huang, J. N. Nkem, and R. A. Sanchez Rodriguez, 2014: Adaptation planning and implementation. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, C.B. Field et al., Eds., Cambridge University Press, 869–898.

Mora, C., and Coauthors, 2017: Global risk of deadly heat. *Nature Climate Change*, **7**, 501–506, https://doi.org/10.1038/nclimate3322.

Noble, I. R., S. Huq, Y. A. Anokhin, J. A. Carmin, D. Goudou, F. P. Lansigan, B. Osman-Elasha, and A. Villamizar, 2014: Adaptation needs and options. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, C.B. Field et al., Eds., Cambridge University Press, 833–868.

Ortman, J. M., V. A. Velkoff, and H. Hogan, 2014: *An aging nation: the older population in the United States*. US Department of Commerce, Economics and Statistics Administration, US …, 1–28 pp.

Peacock, W. G., S. D. Brody, and W. Highfield, 2005: Hurricane risk perceptions among Florida’s single family homeowners. *Landscape and Urban Planning*, **73**, 120–135, https://doi.org/10.1016/j.landurbplan.2004.11.004.

van der Pligt, J., 1996: Risk Perception and Self-Protective Behavior. *European Psychologist*, **1**, 34–43.

Ratnam, J. V, S. K. Behera, S. B. Ratna, M. Rajeevan, and T. Yamagata, 2016: Anatomy of Indian heatwaves. *Scientific Reports*, **6**, 24395, https://doi.org/10.1038/srep24395.

Reid, C. E., M. S. O’Neill, C. J. Gronlund, S. J. Brines, D. G. Brown, A. V. Diez-Roux, and J. Schwartz, 2009: Mapping Community Determinants of Heat Vulnerability. *Environmental Health Perspectives*, **117**, 1730–1736, https://doi.org/10.1289/ehp.0900683.

Reid, C. E., and Coauthors, 2012: Evaluation of a Heat Vulnerability Index on Abnormally Hot Days: An Environmental Public Health Tracking Study. *Environmental Health Perspectives*, **120**, 715–720, https://doi.org/10.1289/ehp.1103766.

Renn, O., 1998: The role of risk perception for risk management. *Reliability Engineering & System Safety*, **59**, 49–62.

Robine, J.-M., S. L. K. Cheung, S. Le Roy, H. Van Oyen, C. Griffiths, J.-P. Michel, and F. R. Herrmann, 2008: Death toll exceeded 70,000 in Europe during the summer of 2003. *Comptes Rendus Biologies*, **331**, 171–178, https://doi.org/10.1016/j.crvi.2007.12.001.

Robinson, G. K., 1991: That BLUP is a Good Thing: The Estimation of Random Effects. *Statistical Science*, **6**, 15–32.

Robinson, P. J., 2001: On the Definition of a Heat Wave. *Journal of Applied Meteorology*, **40**, 762–775, https://doi.org/10.1175/1520-0450(2001)040<0762:OTDOAH>2.0.CO;2.

Safi, A. S., W. J. Jr. Smith, and Z. Liu, 2012: Rural Nevada and Climate Change: Vulnerability, Beliefs, and Risk Perception. *Risk Analysis*, **32**, 1041–1059, https://doi.org/10.1111/j.1539-6924.2012.01836.x.

Schellnhuber, H. J., 1999: ‘Earth system’ analysis and the second Copernican revolution. *Nature*, **402**, C19–C23, https://doi.org/10.1038/35011515.

Schmeltz, M. T., G. Sembajwe, P. J. Marcotullio, J. A. Grassman, D. U. Himmelstein, and S. Woolhandler, 2015: Identifying individual risk factors and documenting the pattern of heat-related illness through analyses of hospitalization and patterns of household cooling. *PloS one*, **10**, e0118958, https://doi.org/10.1371/journal.pone.0118958.

Semenza, J. C., C. H. Rubin, K. H. Falter, J. D. Selanikio, W. D. Flanders, H. L. Howe, and J. L. Wilhelm, 1996: Heat-Related Deaths during the July 1995 Heat Wave in Chicago. *New England Journal of Medicine*, **335**, 84–90, https://doi.org/10.1056/NEJM199607113350203.

——, D. J. Wilson, J. Parra, B. D. Bontempo, M. Hart, D. J. Sailor, and L. A. George, 2008: Public perception and behavior change in relationship to hot weather and air pollution. *Environmental Research*, **107**, 401–411, https://doi.org/10.1016/j.envres.2008.03.005.

Slovic, P., 1987: Perception of risk. *Science*, **236**, 280–285.

Smit, B., and J. Wandel, 2006: Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, **16**, 282–292.

Smith, K., 2013: *Environmental Hazards: Assessing Risk and Reducing Disaster*. 6th ed. Routledge, 504 pp.

Smith, T. T., B. F. Zaitchik, and J. M. Gohlke, 2013: Heat waves in the United States: definitions, patterns and trends. *Climatic Change*, **118**, 811–825, https://doi.org/10.1007/s10584-012-0659-2.

Stafoggia, M., and Coauthors, 2006: Vulnerability to Heat-Related Mortality: A Multicity, Population-Based, Case-Crossover Analysis. *Epidemiology*, **17**, 315–323, https://doi.org/10.1097/01.ede.0000208477.36665.34.

Tierney, K., 2014: *The social roots of risk: Producing disasters, promoting resilience*. Stanford University Press, 1–318 pp.

Tomlinson, C. J., L. Chapman, J. E. Thornes, and C. J. Baker, 2011: Including the urban heat island in spatial heat health risk assessment strategies: a case study for Birmingham, UK. *International Journal of Health Geographics*, **10**, 42, https://doi.org/10.1186/1476-072X-10-42.

Tuholske, C., Caylor, K., Funk, C., Verdin, A., Sweeney, S., Grace, K., Peterson, P., & Evans, T. 2021. Global urban population exposure to extreme heat. *Proceedings of the National Academy of Sciences*, *118*(41). https://doi.org/10.1073/pnas.2024792118

Uejio, C. K., O. V Wilhelmi, J. S. Golden, D. M. Mills, S. P. Gulino, and J. P. Samenow, 2011: Intra-urban societal vulnerability to extreme heat: The role of heat exposure and the built environment, socioeconomics, and neighborhood stability. *Health & Place*, **17**, 498–507, https://doi.org/10.1016/j.healthplace.2010.12.005.

U.S. EPA, 2006: *Excessive Heat Events Guidebook*. 1–52 pp.

——, and CDC, 2016: *Climate Change and Extreme Heat: What You Can Do to Prepare*. 1–18 pp.

Vose, R., D. R. Easterling, K. Kunkel, and M. Wehner, 2017: Temperature changes in the United States. *Climate Science Special Report: Fourth National Climate Assessment, Volume I*, D.J. Wuebbles, D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock, Eds., U.S. Global Change Research Program, 185–206.

Wachinger, G., O. Renn, C. Begg, and C. Kuhlicke, 2013: The risk perception paradox--implications for governance and communication of natural hazards. *Risk Analysis*, **33**, 1049–1065, https://doi.org/10.1111/j.1539-6924.2012.01942.x.

Weber, S., N. Sadoff, E. Zell, and A. de Sherbinin, 2015: Policy-relevant indicators for mapping the vulnerability of urban populations to extreme heat events: A case study of Philadelphia. *Applied Geography*, **63**, 231–243.

White-Newsome, J. L., B. N. Sánchez, E. A. Parker, J. T. Dvonch, Z. Zhang, and M. S. O'Neill, 2011: Assessing heat-adaptive behaviors among older, urban-dwelling adults. *Maturitas*, **70**, 85–91, https://doi.org/10.1016/j.maturitas.2011.06.015.

——, B. Ekwurzel, M. Baer-Schultz, K. L. Ebi, M. S. O'Neill, and G. B. Anderson, 2014: Survey of county-level heat preparedness and response to the 2011 summer heat in 30 U.S. States. *Environmental health perspectives*, **122**, 573—579, https://doi.org/10.1289/ehp.1306693.

Whitman, S., G. Good, E. R. Donoghue, N. Benbow, W. Shou, and S. Mou, 1997: Mortality in Chicago attributed to the July 1995 heat wave. *American Journal of Public Health*, **87**, 1515–1518, https://doi.org/10.2105/AJPH.87.9.1515.

Wilhelmi, O. V, and M. H. Hayden, 2010: Connecting people and place: a new framework for reducing urban vulnerability to extreme heat. *Environmental Research Letters*, **5**, 014021, https://doi.org/10.1088/1748-9326/5/1/014021.

Winter, B., Linear Models and Linear Mixed Effects Models in R with Linguistic Applications. http://arxiv.org/pdf/1308.5499.pdf (Accessed July 5, 2017).

Wolf, J., W. N. Adger, and I. Lorenzoni, 2010: Heat Waves and Cold Spells: An Analysis of Policy Response and Perceptions of Vulnerable Populations in the UK. *Environment and Planning A*, **42**, 2721–2734, https://doi.org/10.1068/a42503.

Wolf, T., and G. McGregor, 2013: The development of a heat wave vulnerability index for London, United Kingdom. *Weather and Climate Extremes*, **1**, 59–68, https://doi.org/10.1016/j.wace.2013.07.004.

Zander, K. K., C. Richerzhagen, and S. T. Garnett, 2019: Human mobility intentions in response to heat in urban South East Asia. *Global Environmental Change*, **56**, 18–28, https://doi.org/https://doi.org/10.1016/j.gloenvcha.2019.03.004.

Zuur, A. F., E. N. Ieno, and C. S. Elphick, 2009: A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution*, **1**, 3–14, https://doi.org/10.1111/j.2041-210X.2009.00001.x.

Table 1. Summary of Sensitivity Factors Known to Influence Extreme Heat Risk

Predictor	Direction (+/-)	Details	References
Age (65+)	+	The elderly face higher risk of negative physiological impacts from exposure to hazard and are more likely to be limited in their ability to access health services due to mobility constraints	Semenza et al. 1996; Cutter et al. 2003; Klinenberg 2003; Stafoggia et al. 2006; U.S. EPA 2006; Harlan et al. 2006; Medina-Ramón et al. 2006; Kovats and Hajat 2008; Anderson and Bell 2009, 2011; Reid et al. 2009, 2012; Johnson et al. 2009; Tomlinson et al. 2011; Uejio et al. 2011; Buscail et al. 2012; Wolf and McGregor 2013; White-Newsome et al. 2014; Ebi et al. 2018; Weber et al. 2015; U.S. EPA and CDC 2016
Gender (male)	+	Men have higher rates of heat-related mortality and morbidity than women in the United States. The higher heat vulnerability among men is likely to be attributed to being active in the heat and a higher level of social isolation.	Semenza et al. 1996; Whitman et al. 1997; Kovats and Hajat 2008; Choudhary and Vaidyanathan 2014; Hess et al. 2014; Schmeltz et al. 2015
Educational attainment	–	Less educated individuals often face greater difficulty in accessing health services and information regarding the nature of the hazard	Cutter et al. 2003; Medina-Ramón et al. 2006; U.S. EPA 2006; Anderson and Bell 2009, 2011; Reid et al. 2009, 2012; Smith 2013, 85–86; IPCC 2014; Ebi et al. 2018; Weber et al. 2015; U.S. EPA and CDC 2016
Race/ethnicity (non-white)	+	Racial and ethnic minority groups often reside in more hazard-prone areas, are predisposed to having less power to cope with negative impacts of hazards due to socioeconomic inequalities, difficulties accessing health services, and limited mobility	Curriero et al. 2002; Cutter et al. 2003; Klinenberg 2003; Anderson and Bell 2009, 2011; Reid et al. 2009, 2012; Wolf and McGregor 2013; Tierney 2014, p. 21; IPCC 2014; Ebi et al. 2018; Weber et al. 2015
Income	–	Individuals with higher incomes have more resources to cope negative hazard impacts	Semenza et al. 1996; Cutter et al. 2003; Klinenberg 2003; U.S. EPA 2006; Kovats and Hajat 2008; Ebi et al. 2018; U.S. EPA and CDC 2016
Work status (disabled)	+	Disabled persons are more susceptible to negative hazard impacts	Semenza et al. 1996; Cutter et al. 2003; Klinenberg 2003, 80–81; U.S. EPA 2006; Kovats and Hajat 2008; Ebi et al. 2018; U.S. EPA and CDC 2016
Household size	±	Smaller households (fewer residents) are more susceptible to social isolation as a source of vulnerability; greater numbers may indicate greater access to resources (reduced vulnerability) or presence of	Semenza et al. 1996; Cutter et al. 2003; Klinenberg 2003; Reid et al. 2009, 2012; Weber et al. 2015

	children (increased vulnerability)	

Table 2. Model results predicting heat wave risk perception index

Fixed effects	**β**	**Lower 95% CI**	**Upper 95% CI**	**Standard Error**
Intercept	42.50	35.99	49.01	3.32
Random effects	**Levels (#)**	**Variance (σ^2)**	**Std. dev. (σ)**	**p**
Residual		548.46	23.42	
Age	5	1.16	1.08	0.0129*
Gender	2	5.38	2.32	0.0000***
Race/ethnicity	5	12.29	3.51	0.0000***
Race/ethnicity : gender	10	0.91	0.95	0.1739
Income	7	13.83	3.72	0.0000***
Education	4	0.14	0.37	0.7604
Work status	5	8.99	2.99	0.0000***
Household size	4	0.33	0.58	0.2436
State	49	5.06	2.25	0.0000***
Region	4	4.99	2.23	0.0011**

Notes: Observations = 8789. *p<0.05, **p<0.01, ***, p<0.001

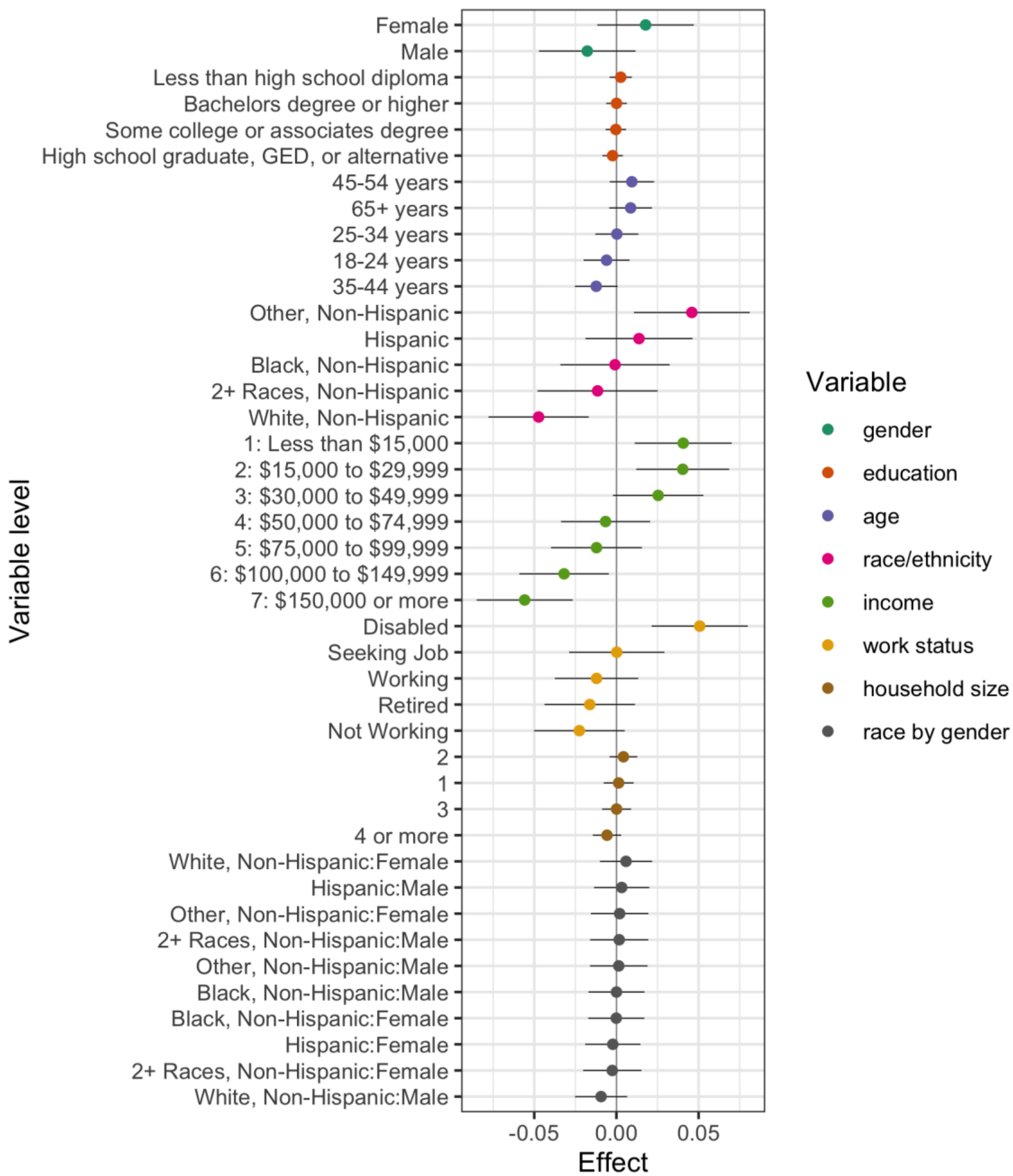

Figure 1. Effects of model predictors with associated 95% confidence intervals, excluding state and region. Points represent best linear unbiased predictor estimates for random effects in multilevel model.

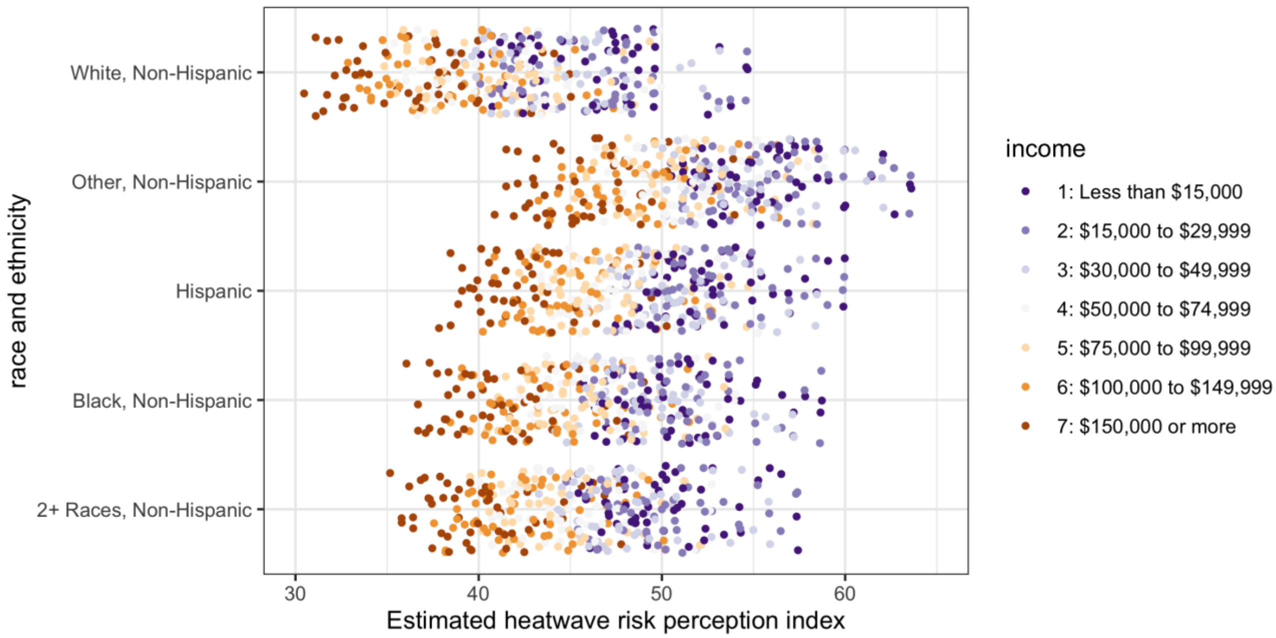

Figure 2. Predicted heat wave risk perception index values for each combination of significant sociodemographic predictors. Each dot represents one type of individual based on each possible permutation of income, race/ethnicity, gender, age, and work status. Dots are ordered by estimated heat wave risk perception index and race/ethnicity.