Heatwaves: A Burning Issue

Assessing the Temporal and Spatial Heterogeneity of Health Impacts from Extreme Heat Exposure among Elderly Populations in the Contiguous U.S. from 2000 to 2016

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Abstract

2023 was the hottest year in recorded history. With the rise in global temperatures due to climate change, we will witness a greater number of sporadic temperature spikes, or "heatwaves", which have a wide range of short- and long-term effects on human health such as heat exhaustion, dehydration, fluid and electrolyte imbalance, and heat stroke. Previous work on the relationship between heatwave exposure and health outcomes has included studying the impact of heatwaves on both mortality and morbidity at varying intervals of time and across varying geographical areas. However, the bulk of the literature lacks a robust assessment of the spatio-temporal heterogeneity in heatwave vulnerability. Our research aimed to examine the heterogeneity in the link between heatwave exposure and hospitalizations for fluid and electrolyte imbalances among Medicare enrollees in the contiguous United States from 2000 to 2016. In particular, we utilized conditional over-dispersed Poisson regression to analyze temporal and spatial variations in heatwave vulnerability. Our most significant finding was that the Northeast (e.g., Vermont, New Hampshire, Maine, Massachusetts, New York), West Coast (California, Washington), and parts of the Midwest (Montana, Colorado, Wisconsin) experienced the greatest relative risk to fluid and electrolyte hospitalizations during a heatwave, which may be driven by infrastructural shortcomings such as a lack of air conditioning. Moreover, although the relative risk of hospitalizations on any day due to fluid and electrolyte imbalances has decreased over the study period, the additional effect of heatwave exposure on the relative risk of hospitalization per year has remained constant. Overall, our research underscores the persistent concern of heat-induced hospitalizations as a pressing issue and confirms that the effects of heatwaves are numerous and diverse. Our study gives an initial insight into where certain populations particularly struggle, but there is still more work to-do to keep all different types of individuals safe from extreme heat and its negative health impacts.

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This thesis is dedicated to my parents. mom and dad, thank you for empowering me to take on any challenge and to pursue the greater good. these ideals guided me throughout this process, and i am so proud of what i was able to accomplish. i am forever grateful for your unwavering support and love as i venture fiercely into my professional and personal adult life. you will always be my heroes, my friends, and my role models.

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"You don't need to be a genius, you don't need to be good at math, and you don't need to suffer to be in science. It's more important that you have the ability to deal with challenges as they come."

Dr. Francesca Dominici

1
Introduction

1.1 Contextualization

2023 was the hottest year in recorded history. According to the Copernicus Climate Change Service [56], "*each month from June to December in 2023 was warmer than the corresponding month in any previous year.*" This news does not come as a surprise, as climate change has been affecting our environment for many years, in the form of rising temperatures, melting ice sheets, rising sea levels, increased extreme weather anomalies, and additional devastating impacts as evidenced by NASA [47]. Unfortunately, we will inevitably continue to see temperatures rise going forward, as the 2023 Emissions Gap Report produced by the UN Environment Programme [66] reported that "*Global Greenhouse Gas emissions set a new record of 57.4 GtCO*$_2$*e in 2022*" (p.XVI), an increase of 1.2% from 2021, and while "*the number of net-zero pledges continues to increase, confidence in their implementation remains low*" (p.XIX). Thus, despite ongoing global efforts to impact the magnitude of climate change, we must consider the scenario that its effects will continue to multiply.

With the overall rise in temperatures, we will also witness a greater number of sporadic temperature spikes, or "heatwaves", defined generally as a short period in time where the daily temperatures exceed a given percentile of the distribution of overall temperatures for a specific geographical region [see, e.g., 2, 4, 12, 44, 69]. According to the WHO [78], "*heatwaves are among the most dangerous of natural hazards, but rarely receive adequate attention because their death tolls and destruction are not always immediately obvious.*"

Heatwaves impact not only our environment but also our human health, and these impacts "*can occur extremely rapidly (same day), or have a lagged effect (several days later)*" [77], thus making them hard to measure in their full scope.

With respect to human health, the WHO reports that:

> "*Exposure to heat causes severe symptoms, such as heat exhaustion and heat stroke, a condition which causes faintness, as well as dry, warm skin, due to the inability of the body to control high temperatures. Other symptoms include swelling in the lower limbs, heat rash on the neck, cramps, headache, irritability, lethargy and weakness. Heat can cause severe dehydration, acute cerebrovascular accidents and contribute to thrombogenesis (blood clots). People with chronic diseases that take daily medications have a greater risk of complications and death during a heatwave, as do older people and children.*" [78]

With such a wide range of effects, heatwaves pose a serious threat to our well-being. In fact, "*between 2000 and 2016, the number of people exposed to heatwaves increased by around 125 million,*" and "*more than 166,000 people died due to extreme temperatures between 1998-2017,*" according to the WHO [78]. These staggering statistics emphasize not only the importance of tackling climate change as a whole but also the need to identify and protect people susceptible to harm.

1.2 Motivation

1.2.1 Heterogeneity in Heatwave Vulnerability

While heatwaves are a global phenomenon, not everyone is impacted equally by them both over time and space. We are therefore particularly interested in both the temporal and spatial heterogeneity of the health effects of heatwaves.

Studying the relationship between heatwave exposure and human health over time can be insightful for two reasons: first, it can provide an understanding of how humans have been impacted by heatwaves historically, and second, it can inform us of how this relationship may have changed in more recent years. For example, it can be informative for policymakers to know if humans have become more or less susceptible to the health impacts over time, so they can determine how best to allocate resources (e.g. if our analyses find that humans have become more susceptible to heatwaves over time, policymakers should direct greater efforts towards public awareness and infrastructural solutions to keep people safe).

In addition, depending on the (i) weather patterns, (ii) geographic and infrastructural characteristics, and (iii) population demographics of a particular location, populations in different areas will experience heatwaves differently and will thus require unique policy and infrastructural changes to keep people safe.

Considering how highly variable weather can be, some individuals may experience heatwaves more frequently based on where they are physically located. According to a Vox article, "*heat waves begin with a high-pressure system (also known as an anticyclone), where atmospheric pressure above an area builds up*". As a result, "*heat waves are especially common in areas that are already arid, like the desert Southwest, and at high altitudes where high-pressure systems readily form*" [65]. Therefore, it is important to study where heatwaves are more likely to occur, so that policymakers can direct their attention and resources toward helping those populations first.

In addition, different locations have different geographical and infrastructural characteristics, which impact how strongly a heatwave is felt by its residents. For example, according to the 2017 Climate Science Special Report by the U.S. Global Change Research Program:

> "*Surface air temperatures are often higher in urban areas than in surrounding rural areas for a number of reasons, including the concentrated release of heat from buildings, vehicles, and industry. This urban heat island effect is expected to strengthen in the future as the structure, spatial extent, and population density*

of urban areas change and grow" [68].

Therefore, urban areas will need extra accommodations during heatwaves, such as more energy efficient buildings and widespread access to air conditioning or cooling centers, as suggested by the CDC [20]. Overall, understanding these disparities with respect to geographic and infrastructural characteristics will allow policymakers to more effectively tailor responses unique to each area.

Population demographics also vary widely by geographic area. For example, Florida has a large elderly population while Massachusetts has a large youth population (due to the large number of Universities in Boston). In addition, socioeconomic and racial demographics vary per geographic area, both of which yield varying experiences of heatwaves. The CDC [19] indicates that the elderly (aged 65+), infants and children, people with chronic medical conditions, low-income individuals, outdoor workers, and pregnant women are all notably vulnerable to extreme heat. Therefore, it is important to study the spatial heterogeneity of heatwaves because, depending on the demographic makeup of each geographic area, policymakers will need to issue specific warnings and disseminate customized preventative information depending on what kinds of individuals constitute the population.

1.2.2 Outcome of Interest

In order to measure the health impacts of heatwaves, we need to select a health outcome of interest. As stated in the Contextualization section, exposure to extreme heat can cause people to become exhausted, dehydrated, and overheated. In more severe cases, people will then undergo heat stroke, which is a dire and potentially deadly physical state.

Thus, a common health outcome associated with heatwaves is heat stroke. However, it is important to emphasize that before succumbing to heat stroke, individuals first experience symptoms of fluid and electrolyte imbalance. According to Johns Hopkins Medicine, when individuals are exposed to extreme heat, they begin to sweat and lose internal fluids, which, when not replaced properly with water, can cause dehydration and electrolyte imbalances. In the event that extreme sweating occurs without proper re-hydration coupled by the body's inability to lower its internal temperature, then heat stroke occurs, a life-threatening condition [36].

Many researchers therefore turn to heat stroke and mortality as the main proxy for heat-related health impacts [3, 4, 7, 8, 13, 24, 32, 38, 44, 45, 49, 50, 55, 69, 69, 71, 75, 76]. However, fluid and electrolyte hospitalizations are even more widespread, as all individuals who experience (and potentially die from) heat stroke first experience fluid and electrolyte imbalance. As a result, fluid and electrolyte hospitalizations are a critical, yet less-frequently investigated, source of heat-related vulnerability.

Therefore, while heat stroke is a serious health effect of heatwaves worth studying, it is more common for an individual to reach the state of fluid and electrolyte imbalance than a state of heat stroke when exposed to a heatwave, so we chose to study the impacts of heatwaves on fluid and electrolyte related hospitalizations.

As a result, the full scope of our research is to assess the relationship between heatwave exposure and fluid and electrolyte hospitalizations among Medicare enrollees in the United States from 2000-2016. Through this research, we aim at identifying temporal and spatial variations in heatwave vulnerability to drive policy and infrastructural response to keep vulnerable individuals and communities safe during heatwaves.

1.3 Reproducibility

For the sake of transparency and reproducibility, we published the R code used to perform our analyses to a public GitHub Repository. We also share the data sources of the publicly available data we used. Since our outcome data (fluid and electrolyte hospitalizations among Medicare enrollees in the U.S.) is human subjects data obtained from the Centers for Medicare and Medicaid Services (CMS), it is considered highly sensitive and cannot be shared due to both contractual Data Use Agreement obligations and IRB requirements.

The public GitHub Repository can be found at:

`https://github.com/danielagarcia319/heatwave-health-effects`.

2

Previous Work and Contributions

2.1 Literature on the Health Impact of Heatwaves

Our research focuses on assessing the relationship between heatwave exposure and fluid and electrolyte hospitalizations among Medicare enrollees in the United States from 2000-2016. To understand the extent of existing work on this topic, we reviewed previous studies linking heatwave exposure to health outcomes (morbidity and mortality), focusing specifically on assessing prior (i) definitions of heatwaves, (ii) spatial and temporal granularity, (iii) health outcomes, and (iv) modeling techniques.

Before discussing each of these categories of previous work, we first want to introduce a few of the studies that guided our research. We will reference these studies in the following sections with respect to various aspects of their designs that we chose to adopt and limitations that we hope to improve upon.

The seminal paper that guided our research design is the 2014 publication by Bobb et al titled "Cause-Specific Risk of Hospital Admission Related to Extreme Heat in Older Adults" [12], which studies heat-related hospitalizations among Medicare enrollees across all U.S. counties from 1999-2010. This paper seeks "*to identify possible causes of hospital admissions during extreme heat events and to estimate their risks using historical data*" (p.1).

Following the Bobb et al 2014 paper, Wang et al (in collaboration with Bobb) published a paper in 2016 titled "Heat stroke admissions during heatwaves in 1,916 US counties for the period from 1999 to 2010 and their effect modifiers" [69], which aimed to perform a similar analysis to the Bobb et al 2014 paper, except that they include only heat stroke-specific Medicare hospitalizations as their outcome (but again study U.S. counties from 1999-2010).

Again citing the 2014 Bobb et al paper, Weinberger et al published a paper in 2021 titled

“Heat warnings, mortality, and hospital admissions among older adults in the United States” [75], which seeks to determine the effect of heat alerts on mortality and hospitalizations among counties in the U.S. from 2006-2016.

Finally, the 2016 Heidari et al paper titled “Susceptibility to Heat-Related Fluid and Electrolyte Imbalance Emergency Department Visits in Atlanta, Georgia, USA” [29] provides an analysis of the relationship between “*warm-season same-day temperatures and fluid and electrolyte imbalance (FEI) emergency department visits using Poisson generalized linear models*” (p.1) from 1993 to 2012.

Throughout the rest of this paper, we will refer to these four studies as Bobb et al 2014, Wang et al 2016, Weinberger at al 2021, and Heidari et al 2016.

2.1.1 Definition of Heatwaves

There is no fixed definition of a heatwave across the literature. A heatwave is generally defined as a short period in time where the daily temperatures exceed a given percentile of the distribution of overall temperatures for a specific geographical region. Overall, most papers tend to define a heatwave as a period of at least 2 or 4 days where the daily average or maximum temperature exceeds the 90th [2, 3, 25, 31, 57, 63, 71], 95th [4, 10, 37, 42, 44, 51, 61, 62, 80], 97th/97.5th [41, 43, 69, 72], or 99th [3, 12, 13, 15, 22, 40, 45, 46, 48, 55, 58, 73] percentile of daily average or maximum temperature for the study region of interest.

More specifically, Bobb et al 2014 defines a heatwave to be “*2 or more consecutive days with temperatures exceeding the 99th percentile of county-specific daily temperatures.*” (p.1) and Wang et al updates Bobb et al 2014’s definition of a heatwave to be “*at least two consecutive days with daily mean temperature greater than the 97th percentile of temperatures* *in that county*", in order to "*capture more heat stroke hospital admissions than other stricter definitions*" (p.2).

Overall, since there are many variations in the definition of a heatwave, we incorporated these variations in our sensitivity analysis to ensure our final selection would not significantly change our results.

2.1.2 Spatial and Temporal Granularity

The impact of heatwaves on health outcomes has been studied thoroughly on a global scale [2, 10, 15, 22, 23, 25, 28, 30, 33–35, 37, 40, 43, 54, 57, 60, 63, 79]. Many studies have focused on the United States in particular [3–5, 7, 8, 11–13, 24, 29, 32, 38, 39, 44, 46, 48–50, 61, 62, 69, 74–76]. These studies vary in their spatial coverage, ranging from a state-specific analysis to nationwide study.

For example, Heidari et al 2016 performs their analysis just on Atlanta, Georgia, which allows them to gain a strong understanding of that particular area, but a limitation of this approach is that the results are not generalizable to the rest of the United States. On the other hand, Bobb et al 2014 and Wang et al 2016 perform their analyses at the county-level across the contiguous U.S., which allows them to yield more generalizable results, but because they do not account for spatial heterogeneity, their results are perhaps *too* generalizable.

In addition, previous studies focus on varying periods in time, from the early 2000s [12, 69] to more recently [75]. However, most of these studies fail to incorporate a broad range of years. For example, Bobb et al 2014 and Wang et al 2016 perform their analyses on data from 1999-2010 and Heidari et al 2016 performs their analysis on data from 1993–2012, while Weinberger et al 2021 performs their analysis on data from 2006-2016. Ideally, we want this research to span both the early 2000s and later 2010s.

2.1.3 Health Outcomes

Previously, researchers have explored the impact of heatwaves on mortality [2–4, 7, 8, 13, 24, 38, 44, 45, 49, 50, 55, 71, 75, 76], heat stroke hospitalizations [32, 69], respiratory disease hospitalizations [5, 40], fluid and electrolyte hospitalizations [29], cardiovascular disease hospitalizations [32, 40], or a wide range of hospitalizations [11, 12, 48, 61, 62, 75, 76].

More specifically, the outcome(s) of interest for Bobb et al 2014 and Weinberger et al 2021 are distinct categories of hospital admission types, formed by grouping ICD-9 codes using the Clinical Classifications Software (CCS), a mapping system that creates a "*smaller number of clinically meaningful categories that are sometimes more useful for presenting descriptive statistics than are individual ICD-9-CM codes*" [26]. On the other hand, Wang et al 2016 uses just hospitalizations classified under the heat stroke ICD-9 code as their outcome, and Heidari et al 2016 uses just the fluid and electrolyte CCS code as their outcome.

A limitation of the studies that just look at mortality as the proxy for heat-related health impacts is that not all people impacted by heatwaves die. As discussed in the Introduction, many individuals experience notable fluid and electrolyte imbalance during heatwaves, which can lead to hospitalization, but are relieved of their symptoms before they progress into a more severe condition such as heat stroke, which can be life-threatening. As a result, measuring heatwave health impacts through mortality leaves out a large percentage of individuals who are still impacted by the heat, just not as severely.

In addition, a limitation on previous studies of morbidity is that they are either too broad or too narrow in their outcomes of interest. For example, Bobb et al 2014 and Weinberger et al 2021 perform their study on a wide array of CCS groups, which provides a series of interesting results, but can be hard to draw clear actions from. Separately, by just looking at heat stroke as the outcome, Wang et al 2016 does not encompass all heat-related health outcomes such as fluid and electrolyte imbalances. Heidari et al 2016 does look at fluid and electrolyte imbalances, but only in Atlanta, Georgia. However, it is important to note that Heidari et al 2016 states that their work "*highlights the utility of fluid and electrolyte imbalance as an indicator of heat morbidity, the health threat posed by warm-season temperatures*" (p.1).

2.1.4 Statistical Methods

The statistical techniques used to conduct these analyses most commonly are distributed lag non-linear [35, 40, 42, 61, 76] over-dispersed and quasi-Poisson [7, 15, 34, 40, 54, 57, 63, 79], and conditional logistic regression modeling [10, 37, 41, 44–46, 55, 60, 61, 80], where the model treats heatwave exposure as a binary or continuous indicator and the outcome as a binary indicator or count of hospitalizations or deaths.

Bobb et al 2014 fits a log-linear mixed-effects regression model stratified by each CCS group, only selecting the groups most relevant to heat-related hospitalizations, and computes the relative risk of hospitalization for that specific disease after heatwave exposure relative to non-heatwave exposure. Bobb et al finds that the following five CCS groups have the greatest relative risk of hospitalization from a heatwave: fluid and electrolyte disorders (CCS 55), renal failure (acute/unspecified, CCS 157), urinary tract infections (CCS 159), septicemia (except in labor, CCS 2), and heat stroke and other external causes (CCS 244). Bobb et al's model contains a binary indicator for heatwave exposure and controls for year and day of the week.

Wang et al 2016 uses a random-effects Poisson regression model with county-level random intercepts to model the relationship between heatwave exposure and heat stroke hospitalization counts, and finds that heat stroke hospitalizations associated with heatwaves declined dramatically over time, indicating increased resilience to extreme heat among older adults. They acknowledge, however, that considerable risks still remain through 2010. Wang et al 2016's model contains the same terms as Bobb et al 2014's model.

Weinberger et al 2021 mimics the same CCS-stratified analysis as Bobb et al 2014 and uses conditional Poisson regression modeling, but uses "*population-weighted daily maximum heat index for each county*" (p.2) as their heat metric. Overall, they find that "*heat warnings were associated with increased risk of hospitalization for heat-related causes,*" (p.1) specifically for the following CCS groups: heat stroke and other external causes (CCS 244), fluid and electrolyte disorders (CCS 55), peripheral vascular disease (CCS 114), renal failure (acute/unspecified, CCS 157), urinary tract infections (CCS 159), septicemia (except in labor, CCS 2), and diabetes mellitus with complications (CCS 50). In their model, Weinberger et al 2021 includes their heat alert treatment variable, stratum indicators for county, and controls for year, day of the week, federal holidays, and lagged daily maximum heat index (lag days 1 and 2). In secondary analyses, they also include one interaction term for time period (2006–2010 vs. 2011–2016) in order to investigate whether the association between heat alerts and health outcomes varies over time.

In Heidari et al 2016, "*associations between warm-season temperatures and FEI ED visits were estimated using Poisson generalized linear models allowing for over-dispersion*" (p.1). They found that "*higher warm-season ambient temperature was significantly associated with*

FEI ED visits, regardless of temperature metric used" (p.1). Their model, in addition to having a continuous treatment variable for heat exposure, has an interaction term for year and the treatment variable and controls for year, day of the week, federal holidays, periods of hospital participation, and average dew point temperature.

A lot of the seminal works in this field, therefore, adopt fairly rudimentary modeling approaches by building regression models with mostly main effects terms and few interaction terms. In doing so, these models do not account for varying types of heterogeneity, such as how the relationship between heatwave exposure and health-outcomes changes over space, which, as discussed in the Introduction, is an important variable through which we need to measure heterogeneity.

2.2 Our Proposed Contributions

Taking into account the previous (i) definitions of heatwaves, (ii) spatial and temporal granularity, (iii) health outcomes, and (iv) modeling techniques, we designed our study so that we could contribute new insights beyond the work of Bobb et al 2014, Wang et al 2016, Weinberger et al 2021, Heidari et al 2016, and others.

First, based on the previous literature, we chose to define a heatwave as a period of 2 or more days where the daily maximum heat index exceeded the 95th percentile of daily maximum heat indices per year. We chose to look at maximum heat index (as opposed to daily average temperature in Bobb et al 2014 and Wang et al 2016) to construct our heatwave indicator. According to the National Weather Service, "*the heat index, also known as the apparent temperature, is what the temperature feels like to the human body when relative humidity is combined with the air temperature,*" [52] which we conclude to be a more accurate reflection of the effect of heat on the human body. Weinberger et al 2021 uses the same metric to measure heat.

Due to the availability of new data, we will perform our analyses on daily data from 2000 to 2016, with the intention of assessing the temporal heterogeneity of hospitalizations after a heatwave. Following the spatial granularity of Bobb et al 2014, Wang et al 2016, Weinberger et al 2021 and others, we chose to conduct our analyses at the county-level for all counties in the contiguous United States, with the intention of then using this data to assess the spatial heterogeneity of hospitalizations after a heatwave.

We hope for our outcome variable to encompass as many Medicare enrollees impacted by heat as possible. So, we selected fluid and electrolyte disorders as our proxy for heat-related health impacts, as it is not only directly related to extreme heat exposure but is widely experienced, both by individuals who succumb to heat stroke and by those who do not.

With respect to modeling, we used the same conditional over-dispersed Poisson regression approach as Weinberger et al 2021. In addition, as mentioned, we want to explore the temporal and spatial heterogeneity of heatwave vulnerability. While Weinberger et al 2021 and Heidari et al 2016 include an interaction term for year in their models, all four studies detailed in this review do not include county or state as a covariate in their models, and therefore their relative-risk results are generalized across their entire geographic region. However, as discussed in the Introduction, not all counties experience or respond to heat equally. Therefore, we will incorporate spatial factors into our modeling to see how the relative risk of fluid and electrolyte hospitalizations for Medicare enrollees differs geographically, in order to more effectively inform policy and infrastructural response.

3

Data

3.1 Data Pipeline

3.1.1 Study Population

Our study population includes Medicare beneficiaries (aged 65+) enrolled in the fee-for-service (FFS) program in the contiguous United States (all U.S. states and Washington D.C., excluding Alaska and Hawaii) from the years 2000-2016. We obtained enrollment and inpatient claims data from the Centers for Medicare and Medicaid Services (CMS) on this specific population, which comprises about 62.9 million distinct individuals across all years. We chose to study this population because the elderly are particularly vulnerable to extreme heat exposure, thus allowing us to conduct a meaningful investigation on the relationship between heat exposure and heat-related health outcomes for these at-risk individuals.

The Medicare denominator data contains metadata for each Medicare enrollee, including their unique QID, ZIP code of residence, age, sex, race/ethnicity, and whether or not they are Medicaid eligible. We then extracted USPS ZIP Code Crosswalk Files from the U.S. Department of Housing and Urban Development's Policy Development and Research Office [67] to link each ZIP code in the CMS denominator data to its appropriate county (FIPS) code.

The Medicare inpatient claims data (MEDPAR data [21]) contains information on up to 25 International Classification of Diseases (ICD) diagnosis codes per hospitalization, to record all identified diagnoses during the visit. The ICD codes are denoted as ICD-9 codes [16] for hospitalizations occurring before October 1st, 2015 and as ICD-10 codes [17] if occurring on or after that date. For our analysis, we chose to study only the primary ICD diagnosis code (of the 25) per hospitalization, otherwise viewed as the primary cause for hospitalization.

As stated previously, our heat-related health outcome of interest is hospitalizations related to fluid and electrolyte disorders, an outcome which was previously identified in Bobb et al (2014) [12] and Weinberger et al (2021) [75] as being associated with heatwave exposure. To comprehensively capture this outcome, we utilized the Clinical Classifications Software (CCS) algorithm developed by the Agency for Healthcare Research and Quality [26], which groups ICD-9 and ICD-10 codes into meaningful disease categories, to identify all fluid and electrolyte disorder related hospitalizations from the primary ICD codes of the inpatient claims from the MEDPAR data (CCS group 55). To efficiently perform these CCS ICD code groupings across our data, we utilized the `icd` R software package [70].

3.1.2 Heat Index

Our exposure variable is the daily maximum heat index per county in the contiguous United States from 2000-2016. This data is obtained from the 2022 Spangler et al publication titled "Wet-Bulb Globe Temperature, Universal Thermal Climate Index, and Other Heat Metrics for US Counties, 2000–2020" [59], which provides "*population-weighted, spatially explicit daily heat metrics*" at the county-level for the contiguous U.S. based on data "*derived from the ERA5-Land gridded data set*" (p.1). We have daily maximum heat index data for 3,103 unique FIPS codes in the U.S., which we used to compute our heatwave treatment variable for our analysis.

3.1.3 Air Conditioning

We acquired air conditioning data for the United States to perform a post-hoc analysis of how air conditioning prevalence is associated with vulnerability to heatwaves. This air conditioning data is sourced from the Romitti et al 2022 publication titled "US Metropolitan Residential Air Conditioning Prevalence", which "*provides empirically-derived probabilities of any (central or room) residential AC for 45,995 census tracts across 115 metropolitan areas in the United States*" [53]. Using the census tract population data provided in this dataset, we computed a population-weighted average air conditioning proportion per state in the contiguous United States. The dataset had data for all states except Idaho, Maine, Montana, North Dakota, South Dakota, Utah, Vermont, and Wyoming.

3.2 Data Wrangling

3.2.1 Data Aggregation

Given our daily maximum heat index data at the county level from 2000-2016, we first computed our binary treatment variable for heatwave exposure. To do so, we grouped our data by year and FIPS code and calculated the 95th percentile maximum heat index for that grouping. Then, we compared each daily maximum heat index value in our data to the 95th percentile value for that county and year, and set an indicator equal to 1 if the daily maximum heat index was greater than the 95th percentile on that day, and 0 otherwise. According to the literature, we chose to classify a heatwave as a period of two or more days where the daily maximum heat index exceeds the 95th percentile. Thus, we created a new indicator variable that was set equal to 1 for a given calendar date if that date was part of a

2+ day period where the maximum heat index exceeded the 95th percentile, and 0 otherwise. In addition, to use for our matching procedure later on, we created a third indicator variable for each calendar date that was set equal to 1 if the date was within three days of a heatwave event, and 0 otherwise.

With our Medicare denominator data, we extracted the number of unique enrollees (denoted by their `qid`) in the contiguous United States from 2000-2016. Using the ZIP code associated with each patient, we joined the FIPS codes associated with each ZIP code from the USPS ZIP Code Crosswalk Files to the denominator data. Then, we grouped our data by FIPS code and year and counted the distinct number of enrollees (`qids`) to determine the total Medicare population in each group.

We then filtered our Medicare inpatient claims data for patients present in our filtered Medicare denominator data (residing in the contiguous U.S. between 2000-2016). We used the `icd` R package to determine which Clinical Classification Software (CCS) group the primary diagnosis ICD code (`DIAG1`) of each hospitalization observation belonged to and filtered for observations whose primary diagnosis code belong to category 55 (*fluid and electrolyte disorders*). Then, we grouped the data by FIPS code and calendar date and summed the total number of fluid and electrolyte hospitalizations to get our outcome variable for our study. [1]

The air conditioning prevalence data is at the census-tract level but also included the population count and state code for each observation, so we grouped the data by state code,

[1] It is worth noting that we did not perform a sensitivity analysis to the choice of using just the primary diagnosis ICD code to categorize our hospitalizations. We could have taken into account all secondary diagnoses to see if fluid and electrolyte disorders were diagnosed during the hospital visit. However, we found that most previous work looks at just the primary code to classify hospitalizations, and there is a possibility that a secondary fluid and electrolyte disorder diagnosis may not be a strong enough signal of a heat-related health effect.

summed the population within each county, and computed a population-weighted mean air condition prevalence per state for our post-hoc vulnerability analysis.

Having aggregated the heatwave (treatment), hospitalizations (outcome), Medicare denominator, and air conditioning data individually, we then left-joined the denominator and hospitalizations data to the heatwave data. The hospitalization data was joined by FIPS code and calendar date, the Medicare denominator data was joined by FIPS code and year, and the air conditioning data was joined by the state code. This aggregated dataset would serve as the foundation for our study.

3.2.2 Creating a Matched Dataset

To properly measure the effect of heatwave exposure on the number of fluid and electrolyte hospitalizations per county, we used our previously aggregated data set to create a 1-to-1 matched data set with equal counts of treatment and control observations. We followed the same matching procedure as in Bobb et al 2014 [12] by matching each heatwave day within each county to a non-heatwave day in that county within three calendar days of the heatwave date but in a different year, assuring that the non-heatwave day was not within three days of a separate heatwave event.

Our matching procedure notably differed from the one proposed in Bobb et al 2014 in that we considered all days of a heatwave event (including the first day) as a "heatwave day", whereas Bobb et al considered only the second through last day of a heatwave event as a "heatwave day". In doing so, Bobb et al did not take any hospitalizations on the first day of a heatwave into account for their analysis. However, according to Dr. Corey Slovis, Professor of Emergency Medicine and Internal Medicine at Vanderbilt Medical Center, "*Heat* *can sometimes be very subtle in how it affects the body. If you're out in the sun, it can take just 30 minutes or up to a few hours for the heat to cause dehydration, nausea or trouble concentrating*" [27]. The WHO confirms this, by stating that "*Deaths and hospitalizations from heat can occur extremely rapidly (same day), or have a lagged effect (several days later) and result in accelerating death or illness in the already frail, particularly observed in the first days of heatwaves*" [77]. Therefore, we chose to include the first day in our analysis, as symptoms of heat-related illness can take effect quickly.

3.3 Exploratory Data Analysis

After generating our final matched data set, we performed some spatial Exploratory Data Analysis (EDA) to get a better understanding of how our data varies across the United States.

We began by mapping two heatwave metrics per county: (i) the total number of heatwave events and (ii) the total number of heatwave days. In our definition, introduced above, a heatwave event is defined as a period of 2 or more days where the maximum heat index exceeds the 95th percentile maximum heat index per county and year. A heatwave day is any one day that is a part of a heatwave event.

Figure 3.3.1 displays the total number of heatwave events per county in the Contiguous U.S. from 2000-2016, where the number of events ranged from 46 to 94 across all counties. We can see that the Northeast, Midwest, Coastal West, and parts of the Mid-South experienced the greatest number of heatwave events according to our definition.

Figure 3.3.2 displays the total number of heatwave days per county in the contiguous

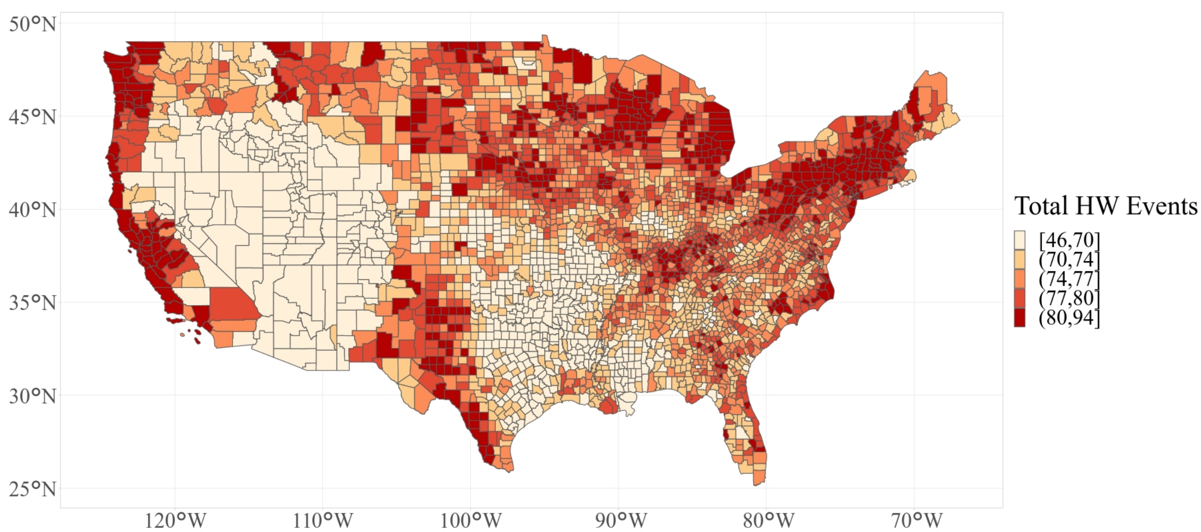


Figure 3.3.1: Total Heatwave Events per County from 2000-2016 in the Contiguous U.S. Using a 95th Percentile Heat Index Threshold.

U.S. from 2000-2016, where the number of days ranged from 196 to 299 across all counties. It is interesting to note that there is somewhat of an inversion in this map from the heatwave events map, suggesting that the areas with a greater number of heatwave events experienced heatwaves that were shorter in duration, while the areas that experienced a fewer number of events experienced heatwaves that were longer in duration. This phenomenon has different implications for how to best keep people safe from the negative health impacts of heatwaves, depending on whether individuals need to plan for fewer heatwaves of long duration or more frequent heatwaves of shorter duration.

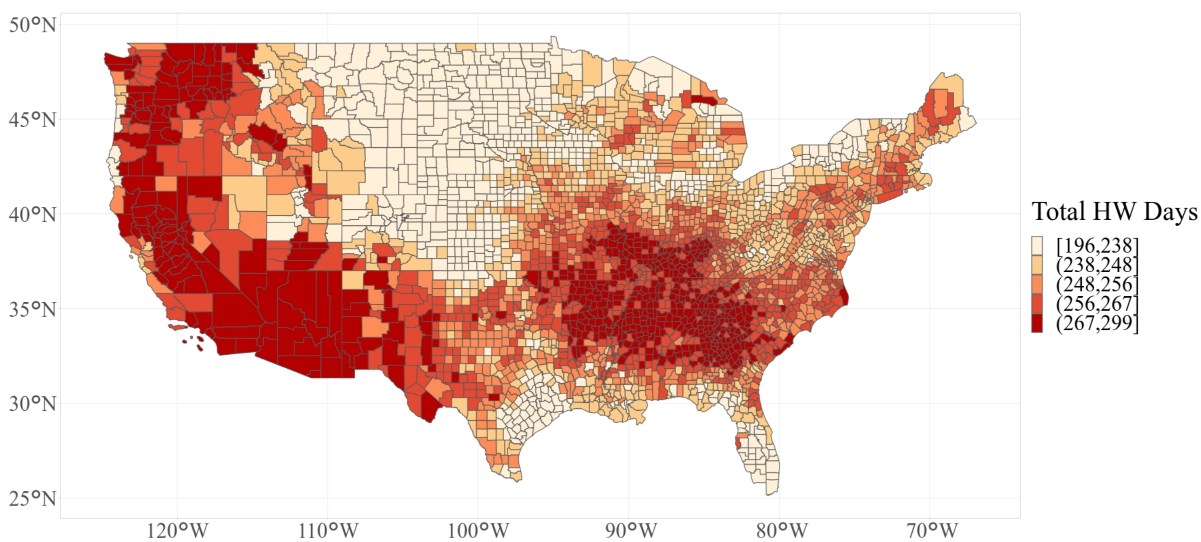


Figure 3.3.2: Total Heatwave Days per County from 2000-2016 in the Contiguous U.S. Using a 95th Percentile Heat Index Threshold.

Next, to better understand the distribution of our study population, we created a map of the number of Medicare enrollees per county in the contiguous U.S. in 2016, where the minimum number of enrollees per county is 10, and the maximum number of enrollees per county is 602,387. We see in Figure 3.3.3 that the largest populations of enrollees are in the West Coast, in Florida, and in the Mid-Atlantic/Northeast, keeping in mind that these areas are also more populous overall.

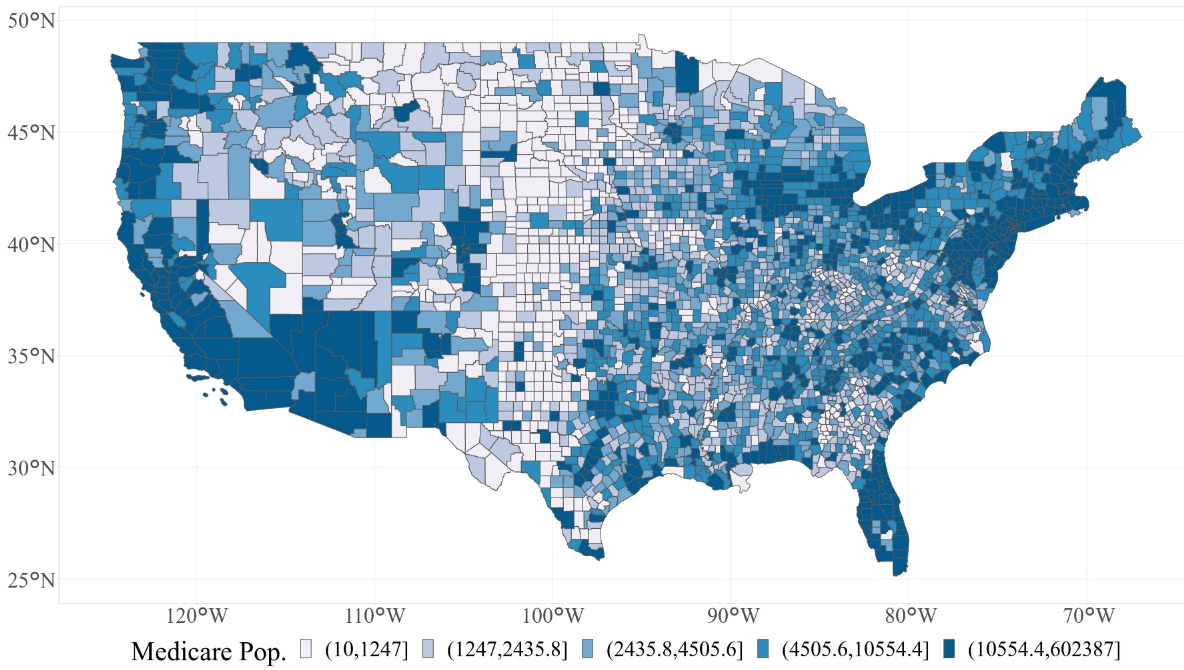


Figure 3.3.3: Medicare Enrollee Population per County in 2016 in the Contiguous U.S.

We then created a map of the total number of fluid and electrolyte hospitalizations per county in the contiguous U.S. from 2000-2016, where the minimum number of hospitalizations per county is 0 and the maximum number is 6,034. Similarly to our conclusions about the Medicare enrollee population, we observe in Figure 3.3.4 that the greatest quantity of fluid and electrolyte-related hospitalizations is on the West Coast, in Florida, and in the Mid-Atlantic/Northeast, which correlates with their larger population sizes in these regions.

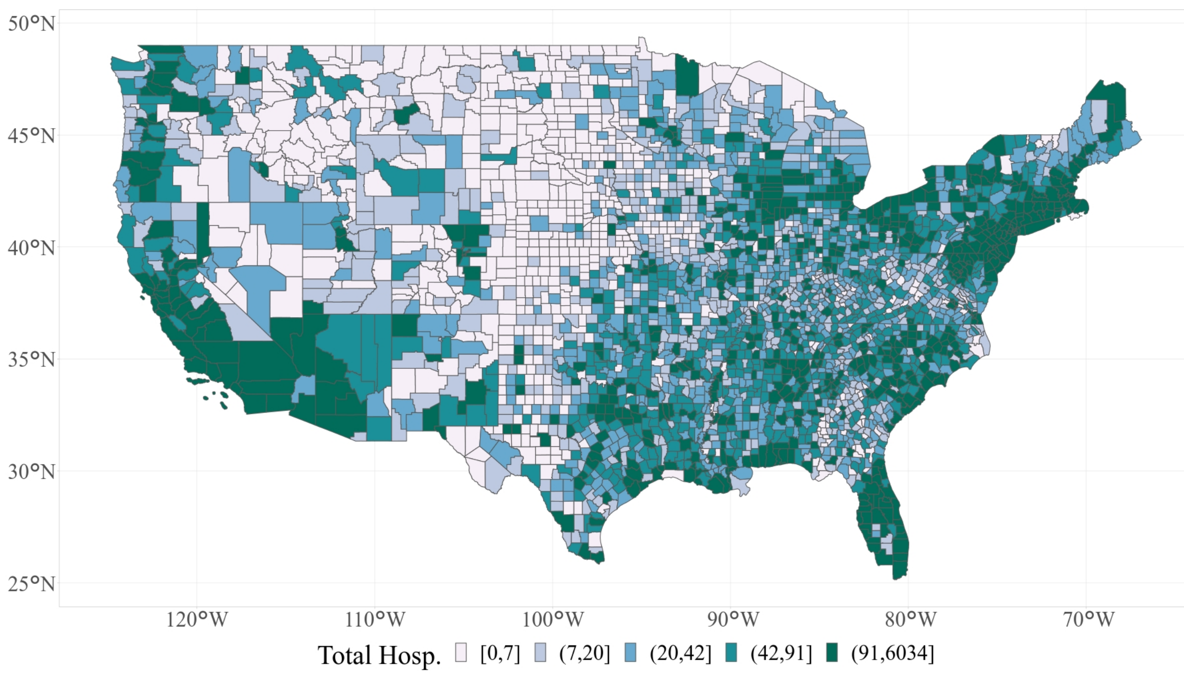


Figure 3.3.4: Total Fluid and Electrolyte Hospitalizations from 2000-2016 among Medicare Enrollees in the Contiguous U.S. Using a 95th Percentile Heat Index Threshold.

Finally, considering that the distribution of the Medicare enrollee population is not even across all counties, we created a map of the total number of fluid and electrolyte hospitalizations *per 100,000 Medicare enrollees* per county in the contiguous U.S. from 2000-2016, where the minimum hospitalization rate is 0 and the maximum hospitalization rate is about 5430 enrollees per 100k. We see in Figure 3.3.5 that the highest rates of hospitalization relative to the Medicare enrollee population size occur in the South and in the Mid-Atlantic/Northeast. Interestingly, in this case, Florida does not exhibit the highest *rates* of hospitalization, despite having a high number of hospitalizations overall. This reflects the notion that Florida has a larger enrollee population, so their rate of hospitalization is proportional to that size.

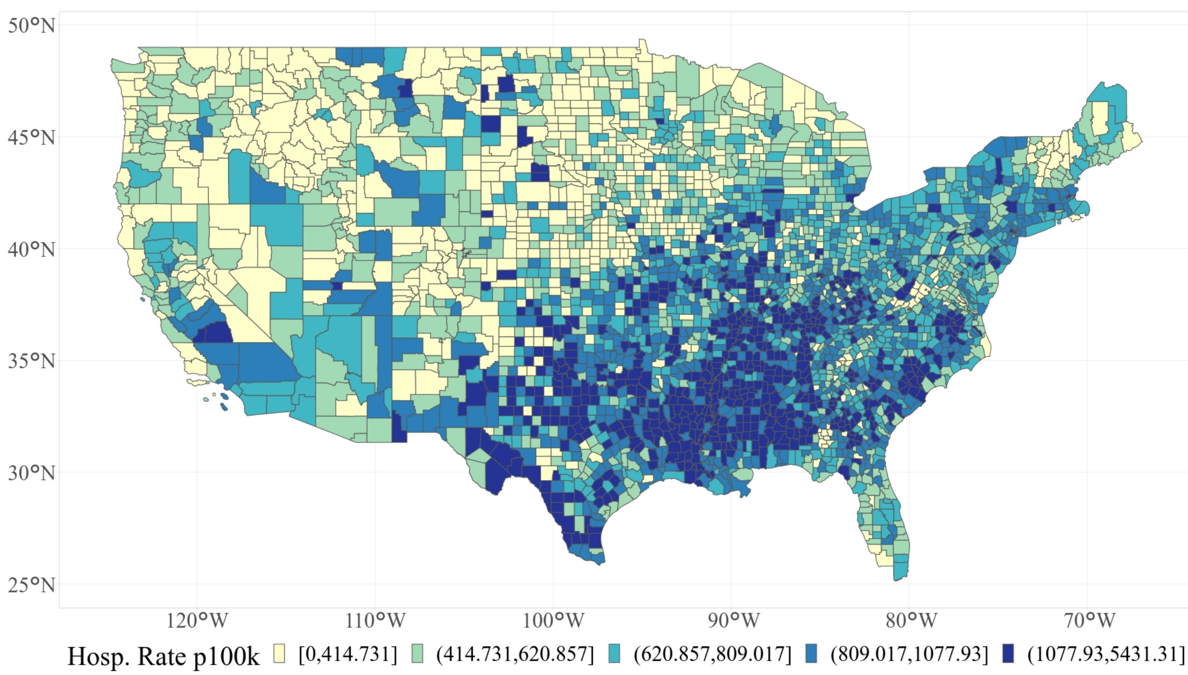


Figure 3.3.5: Total Fluid and Electrolyte Hospitalizations per 100k Medicare Enrollees from 2000-2016 in the Contiguous U.S. Using a 95th Percentile Heat Index Threshold.

4

Methods

4.1 Models Employed in the Literature

As discussed in the Literature Review section, our matched dataset contains a binary treatment indicator for a heatwave day, an outcome variable measuring the number of hospitalization counts, and a set of covariates. The utilization of regression techniques to analyze this relationship has been a common approach in prior studies, such as the adoption of distributed lag non-linear models often for continuous treatment variables [35, 40, 42, 61, 76] and conditional logistic regression modeling for individual-level datasets [10, 37, 41, 44–46, 55, 60, 61, 80]. In some instances, depending on the distribution of the hospitalization counts, researchers have opted for quasi-Poisson, over-dispersed, or negative-binomial modeling to more accurately model the relationship [7, 15, 34, 40, 54, 57, 63, 79].

4.1.1 Mixed-Effects Regression Models

We started our modeling approach by recreating the model from Bobb et al 2014 [12] to (a) confirm the likeness of our matched data set to theirs and to (b) observe how the coefficients from the original model might have changed as more recent data was added.

Bobb et al fit a mixed-effects Poisson regression model to their data. Their model is as follows:

$$\log E(Y_t^c) = \log(n_t^c) + \alpha + \alpha^c + \beta hw_t^c + \sum_{j=1}^{6} \gamma_j dow_{jt} + \sum_{k=1}^{16} \delta_k year_{kt}, \tag{Bobb et al 2014}$$

where Y_t^c is the number of hospitalizations on day t in county c, n_t^c is the number of individuals at risk (i.e. Medicare population), $\alpha^c \sim N(0, \sigma^2)$ is a county-specific random intercept to account for within-county correlation of the observations, and hw_t^c is an indicator for whether the day is a heatwave versus non-heatwave day. The model is also adjusted for the day of the week and for the study year, both as categorical variables, where dow_{jt} ($j = 1, ..., 6$) are indicator variables for the day of the week, and $year_{kt}$ ($k = 1, ..., 16$) are indicator variables for study year.

As our dataset contained a large number of observations where the hospitalization count was 0, we decided to utilize a mixed-effects Negative Binomial regression to account for the inflation in the 0 label. The proposed mixed-effects Negative Binomial model used the same terms as the Bobb et al model but using Negative Binomial as the family for our outcome variable. So, we can represent our outcome variable Y_i as the following, where i is the specific county, as described in Booth et al [14]:

$$Y_{ij}|\mathbf{u}_i \sim \mathrm{nb}(\alpha, \mu_{ij}) \text{ with } \mu_{ij} = \mathrm{E}(y_{ij}|\mathbf{u}_i) = \exp\{\mathbf{x}'_{ij}\boldsymbol{\beta}_m + \mathbf{z}'_{ij}\mathbf{u}_i\},$$

where $\boldsymbol{\beta}_m$ is an unknown vector of regression coefficients and $\mathbf{u}_i$ is a vector of county-specific Normally-distributed random effects. In this case, the subscript m stands for mixed-effects modeling. This model was implemented using the `glmer.nb` function from the `lme4` R package [9].

4.1.2 Fixed-Effect Regression Models

Fitting a mixed-effects model allows us to account for within-county variability, but it can also pose some computational challenges, as fitting the county-specific coefficients requires additional resources, making it costly and time-consuming. As a result, we also fit a fixed-effects regression model. Similarly to Weinberger et al [75], we utilized an over-dispersed fixed-effects conditional Poisson regression model to assess the relationship between heat alerts and the number of heat-related health outcomes within counties:

$$\log E(Y_t) = \log(n_t) + \alpha + \beta hw_t + \sum_{j=1}^{6} \gamma_j dow_{jt} + \sum_{k=1}^{16} \delta_k year_{kt}. \qquad \text{(Model 1)}$$

We used the `gnm` package [64] to fit this over-dispersed fixed-effects conditional Poisson regression model, which we labeled as Model (1), which proves to be very computationally effective as a result of the `exclude` argument present in their `gnm()` model function.

4.2 Our Models

The models introduced in the previous section, which directly follow the current literature on the assessment of health effects of heat waves, enable us to explore whether there is a statistically significant increase in the relative risk of fluid and electrolyte hospitalizations on heatwave days as opposed to non-heatwave days. However, in our research, we seek to extend this analysis further to assess how these results vary temporally and geographically.

The benefit of extending this analysis is that we can better understand how the number of hospitalizations during heatwaves changes both over time and across different geographic areas of the contiguous United States, which will give us a more comprehensive understanding of where the greatest vulnerabilities lie among our population (e.g. the South versus the Northeast, etc.). By measuring these heterogeneities more explicitly in our models, we can provide more specific conclusions about different sub-populations, which will better inform how to effectively approach heatwaves on a case-by-case basis, as opposed to a one-size-fits-all solution. With this goal, we fit three additional over-dispersed fixed-effects conditional Poisson models.

The first new model we fit is intended to see how the relative risk of hospitalization changes per year by adding an interaction term with our treatment variable and year variable, which we will call Model (2). This model does not include any other covariates, as we wanted to assess this relationship across all geographic locations and days of the week. The model takes the following form:

$$\log E(Y_t) = \log(n_t) + \alpha + \beta hw_t + \sum_{k=1}^{16} \delta_k year_{kt} + \sum_{l=1}^{16} \rho_l year_{lt} * hw_t. \qquad \text{(Model 2)}$$

The next new model we fit is intended to investigate how the relative risk of hospitalization changes across states in the contiguous U.S. by adding a main effect categorical variable for each state and an interaction term between each state and the treatment variable, which we will call Model (3). We wanted our geographic variable to be at the county-level, but due to computational restraints, we fit the model at the state level. We also did not include the year or day of the week in this model, as we wanted to generalize our results across all years and days of the week within each state. The model takes the following form:

$$\log E(Y_t) = \log(n_t) + \alpha + \beta hw_t + \sum_{k=1}^{49} \delta_k state_{kt} + \sum_{l=1}^{49} \rho_l state_{lt} * hw_t. \qquad \text{(Model 3)}$$

The last new model we fit is intended to include both the temporal and geographical variation in the relationship between heatwave exposure and fluid and electrolyte hospitalizations. As a result, this model includes the same terms from Model (1), in addition to our new main effect term for each state and the two interaction terms between year and the treatment variable and between state and the treatment variable. This model would theoretically give us the most granular relative risk results to draw conclusions from the data, and it takes the following form:

$$\log E(Y_t) = \log(n_t) + \alpha + \beta hw_t + \sum_{j=1}^{6} \gamma_j dow_{jt} + \sum_{k=1}^{16} \delta_k year_{kt} + \\ + \sum_{l=1}^{16} \rho_l year_{lt} * hw_t + \sum_{m=1}^{49} \gamma_m state_{mt} + \sum_{n=1}^{49} \phi_n state_{nt} * hw_t. \quad \text{(Model 4)}$$

To perform these analyses we used the `gnm` R package.

4.3 Sensitivity Analysis

In response to the design decisions we made for this analysis, we performed a sensitivity analysis to assess the robustness of our results subject to changes in the study design. The main area of flexibility with respect to the study design for this type of analysis is our definition of a heatwave. As discussed in the literature review, there is no formal, rigid definition of a heatwave, which presented us with the opportunity to choose how we wanted to define a heatwave based on our project scope and goals.

We found that a majority of studies chose a period of two or more days as the duration of a heatwave, but there was more variability in the binary percentile threshold chosen. As a result, we decided to produce a sensitivity analysis not on our chosen duration of a heatwave but instead on our percentile threshold. As a result, in addition to running our main analysis using a threshold at the 95th percentile, we ran our sensitivity analysis using a threshold at the 97th percentile. We reproduced all of the same models and figures as in the main analysis and included them in the Appendix.

5
Results

Table 5.1.1: Comparing Matched Data Set Results Between Bobb et al 2014 and Our 95th and 97th Percentile Heat Index Data.

		Total No. of Admissions		Daily Admission Rate, No. per 100k Individuals at Risk (95% CI)			
Source	Total Heatwave Days	Matched Non-Heat Wave Days	Heat Wave Days	Matched Non-Heat Wave Days	Heat Wave Days	Risk Difference (95% CI)	Relative Risk (95% CI)
Bobb et al 2014		9,354	11,382	1.85 (1.63-2.09)	2.19 (1.95-2.45)	0.34 (0.32-0.36)	1.18 (1.17-1.20)
Our data (95%)	779,978	120,586	137,123	1.66 (1.64-1.68)	1.88 (1.85-1.91)	0.22 (0.21-0.23)	1.13 (1.13-1.14)
Our data (97%)	411,854	54,371	73,092	1.45 (1.42-1.48)	1.88 (1.85-1.91)	0.43 (0.43-0.43)	1.30 (1.29-1.30)

5.1 Results from Updating Previously Published Models

Once we generated our matched data set, we recreated the statistics in Figure 2 of the Bobb et al 2014 [12] paper,[1] which include the total number of fluid and electrolyte hospitalizations on a heatwave day and on a non-heatwave day, the daily admission rate per 100,000 Medicare enrollees on a heatwave day and on a non-heatwave day, and the risk difference and relative risk of daily admission rates between heatwave days and non-heatwave days. We report these results in Table 5.1.1.[2]

[1] Note that Bobb et al 2014 reported results for the period 1999 to 2010 while our analyses span the period from 2000 to 2016.

[2] It is important to re-state the differences between the matching processes in the Bobb et al 2014 paper and our research. Bobb et al 2014 performed matching for heatwave days that were the second or later day within a heatwave event, where a heatwave event is defined as a period of 2 or more days where the daily average temperature exceeds the 99th percentile of daily average temperatures per county and year from 1999-2010. We, on the other hand, including all days of a heatwave (including the first day) for our matching process, where we defined a heatwave as a period of 2 or more days where the daily maximum temperature exceeded the 95th (and 97th, for sensitivity analysis) percentile of daily maximum heat indices per county and year from 2000-2016.

Based on Table 5.1.1, our results do not stray too far from Bobb et al 2014's figures, despite having different definitions for heatwaves. It is worth noting that our 97th percentile data set yielded a notably high relative risk of fluid and electrolyte hospitalization (RR = 1.30), which highlights the pertinence of our topic, especially for more stringent heatwave thresholds. It makes sense that the 95th percentile data yielded the lowest risk difference and relative values, because it includes data on less intense heatwaves.

After comparing these initial statistics, we then sought to re-create the model from Bobb et al 2014 using our new data and new modeling approaches. As mentioned in the Methods section, we fit two regression models with the same terms as Bobb et al's: a mixed-effects Negative Binomial model and a fixed-effects over-dispersed conditional Poisson model. The coefficients (with standard errors and significance values) of these two models are reported in Table 5.1.2.

As displayed in Table 5.1.2, the treatment coefficient estimates between the two models are very similar, providing justification for using just the over-dispersed conditional Poisson model in subsequent analysis (which is a more computationally efficient model).

Notably, the estimated coefficient for the heatwave (treatment) variable is 0.086 for the Negative Binomial model and 0.087 for the over-dispersed conditional Poisson model, with both estimates being statistically significant at the $p < 0.001$ significance level. These two coefficient estimates correspond to a relative risk of `exp(0.086) = 1.090` and `exp(0.087) = 1.091` of fluid and electrolyte hospitalization on a heatwave day versus a non-heatwave day, respectively. Therefore, these initial models reveal that there is a statistically significant increase in the relative risk of fluid and electrolyte hospitalizations on a heatwave day versus non-heatwave day in the contiguous U.S., controlling for day of the week and year.

Table 5.1.2: Recreating Bobb et al 2014's Model with a Negative Binomial Model (`glmer.nb`) and Overdispersed Conditional Poisson Model (`gnm`) Using 95th Percentile Heat Index Data.

	Negative Binomial Model	Conditional Poisson Model
(Intercept)	-11.057^{***}	
	(0.013)	
Heatwave (Treatment)	0.086^{***}	0.087^{***}
	(0.004)	(0.004)
Includes `Day of the Week`	Y	Y
Includes `Year`	Y	Y
Observations	1,559,956	1,559,956

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

It is important to note that these models do not account for any interactions between space and time and the treatment variable, which has motivated us to fit additional models looking at the interaction between `year` and the heatwave treatment indicator and between `state` and the heatwave treatment indicator.

5.2 Extending Previous Models

To gain more insight into the temporal and spatial vulnerability to fluid and electrolyte hospitalizations on a heatwave day, we fit three subsequent over-dispersed conditional Poisson regression models that include just `year` as a main effect and interaction term with our heatwave indicator labeled Model (2), just `state` as a main effect and interaction term with our heatwave indicator labeled Model (3), and both `year` and `state` as main effect terms and interaction terms with our heatwave indicator, with the day of the week as a control labeled Model (4).

The estimated coefficients of these three additional models, plus Model (1) as the original over-dispersed conditional Poisson model from the previous section, are displayed in Table 5.2.1. In this table, we report only the treatment coefficients and not the controls or interaction terms (to save space), but the full table of coefficients can be found in the Appendix in Table A.1.2.[3]

Across all four models, the coefficient for the heatwave (treatment) variable are very similar and all statistically significant at the $p < 0.01$ significance level, regardless of the inclusion of various spatial and temporal controls and interaction variables.

Table 5.2.1: Comparing Over-dispersed Conditional Poisson Models (1), (2), (3), (4) Using 95th Percentile Heat Index Data.

	Model			
	(1)	(2)	(3)	(4)
Heatwave (Treatment)	0.087^{***}	0.081^{***}	0.089^{***}	0.073^{**}
	(0.004)	(0.014)	(0.025)	(0.027)
Includes `Day of the Week`	Y	N	N	Y
Includes `Year`	Y	Y	N	Y
Includes `Heatwave:Year` Treatment	N	Y	N	Y

[3]For all tables, we did not report the main effects coefficients for the `state` variable, as they yielded non-interpretable results (0.0 point estimate and NA for standard error).

	(1)	(2)	(3)	(4)
Includes `Heatwave:State` Treatment	N	N	Y	Y
Observations	1,559,956	1,559,956	1,559,956	1,559,956

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

In the following two sections, we will assess the interaction terms of `year` with our treatment indicator and `state` with our treatment indicator, in order to better assess the heterogeneity of relative risk to fluid and electrolyte hospitalizations on heatwave versus non-heatwave days across time and space.

5.2.1 Temporal Heterogeneity

After observing the main effects coefficients of `year` in Models (2) and (4), we wanted to explore the coefficients of the interaction terms between year and heatwave exposure for each of these two models.

To do so, we generated two time-series graphs of the coefficients for each model in Figure 5.2.1, where each time-series reports the main effect coefficient for each year (labeled `main effect`), the coefficient of the interaction term between the heatwave treatment indicator and year (labeled `interaction`), and the sum of the main effect and treatment coefficient per year (labeled `main effect + interaction`). All coefficients are reported in terms of relative risk.

This time-series will allow us to assess two trends: (1) how the relative risk of fluid and electrolyte hospitalizations on non-heatwave days has changed over time (as shown by the green `main effect` line) and (2) how the relative risk of hospitalization on a heatwave day versus non-heatwave day has changed over time (as shown by the blue `interaction` and red `main effect + interaction` lines).

In Figure 5.2.1, we first see that the two time-series graphs are very similar, indicating that the main effects and interaction terms for our treatment indicator and year did not change significantly when controlling for the interaction between our treatment indicator and state.

In both time-series, we see that, while the relative risk of fluid and electrolyte hospitalization on any day has decreased steadily over time (as shown by the decreasing green and red lines), the relative risk of hospitalization has been shown to be slightly higher on heatwaves days than on non-heatwave days (as shown by the red line hovering slightly above the green line) approximately during the years 2003-2014. Overall, the incremental impact attributed to the interaction between the heatwave day and the year indicator remains constant throughout our study period (as shown by the blue line). It is, however, worth noting the fact that our data ends at 2016, and it is therefore possible that these relationships have changed in most recent years.

5.2.2 Spatial Heterogeneity

We also explored the the spatial heterogeneity of the relative risk of fluid and electrolyte hospitalizations on heatwave versus non-heatwave days by looking at the coefficients of our state and heatwave interaction terms for Models (3) and (4) both controlling and not controlling for year and day of the week.

To illustrate these disparities, we first created a map of the relative risks of fluid and

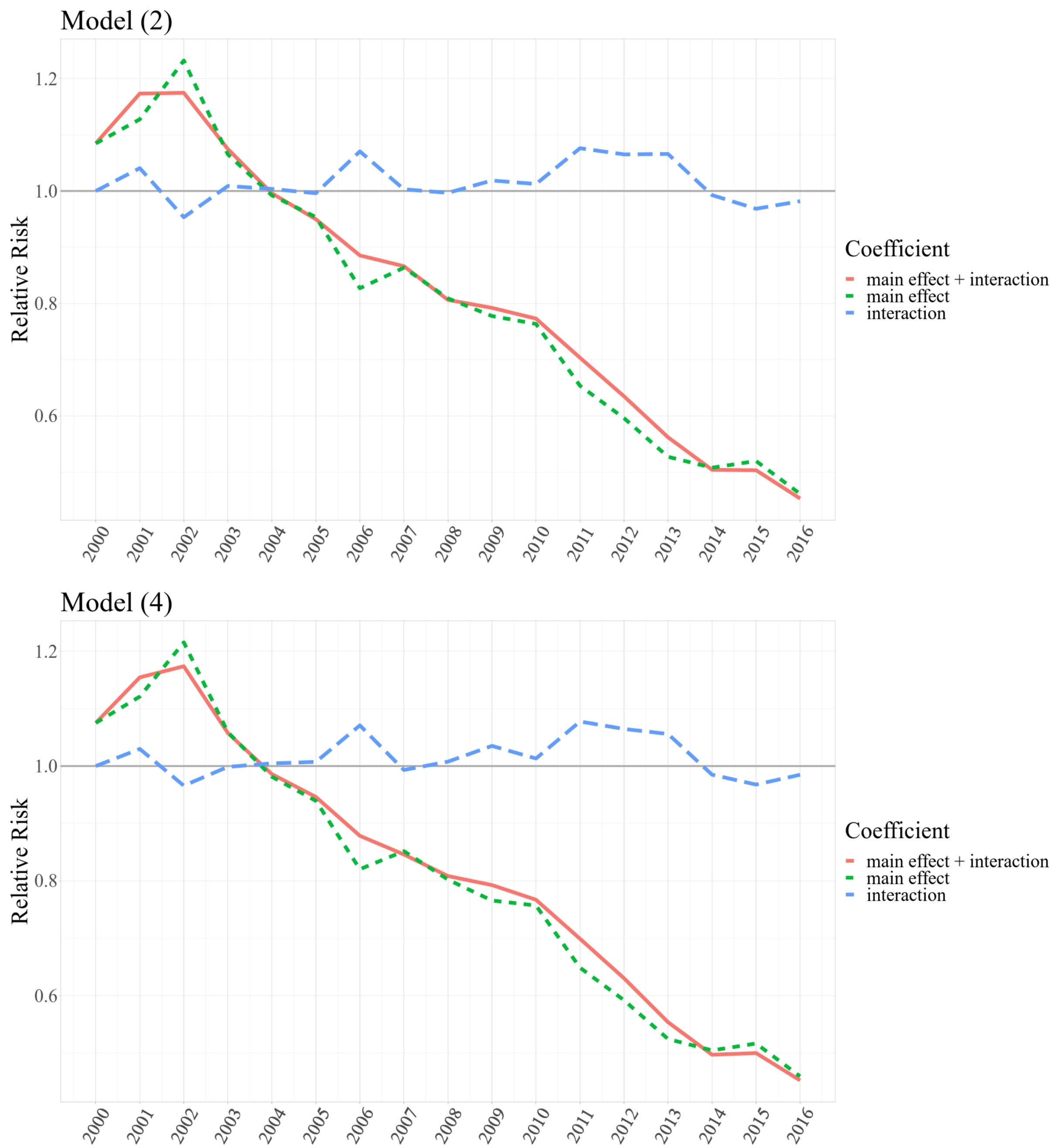


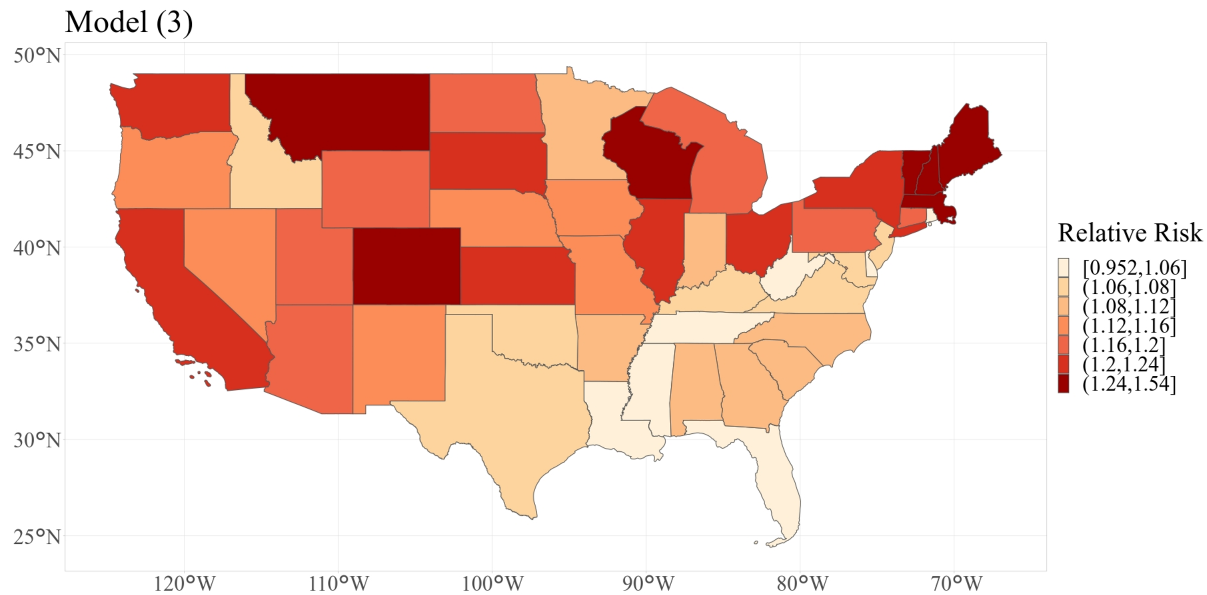
Figure 5.2.1: Relative Risk of Fluid and Electrolyte Hospitalization Over Time from 2000-2016 in the Contiguous U.S., both Controlling and Not Controlling for a Heatwave Day Using a 95th Percentile Heat Index Threshold.

electrolyte hospitalization per state for both Model (3) and Model (4) in Figure 5.2.2. We mapped the relative risk values on a discrete scale to make the colors on the map easier to interpret, where a darker red color indicates a higher relative risk and a lighter orange color indicates a smaller relative risk.

Next, to understand which states were most and least vulnerable to fluid and electrolyte hospitalizations on heatwave versus non-heatwave days, we produced a bar-plot of the relative risk of hospitalization per state (with 95% confidence intervals) for the ten highest and ten lowest states, as seen in Figure 5.2.3.

Based on Figure 5.2.2, we see that the Northeast, parts of the Midwest, and the West Coast have the highest relative risk values overall and therefore exhibit the strongest vulnerability to heatwaves with respect to fluid and electrolyte hospitalizations. It is interesting to see that, relative to the rest of the contiguous U.S., the South is not as vulnerable, likely due to infrastructural differences (the South is more accustomed to hot weather and thus has the appropriate air conditioning and cooling resources).

Figure 5.2.3 shows that the states with the highest relative risk values (included in both models) are Wisconsin, Maine, Massachusetts, Montana, New Hampshire, and Vermont (highest), while the states with the lowest relative risk values (included in both models) are Tennessee, Florida, West Virginia, Louisiana, Missouri, and Delaware. The confidence intervals in this bar plot show more statistical significance for states with high relative risk but no statistical significance for states with low relative risk, thus demonstrating that we are fairly confident about which states are notably more vulnerable to fluid and electrolyte hospitalization on heatwave days versus non-heatwave days, but have no statistically signif-



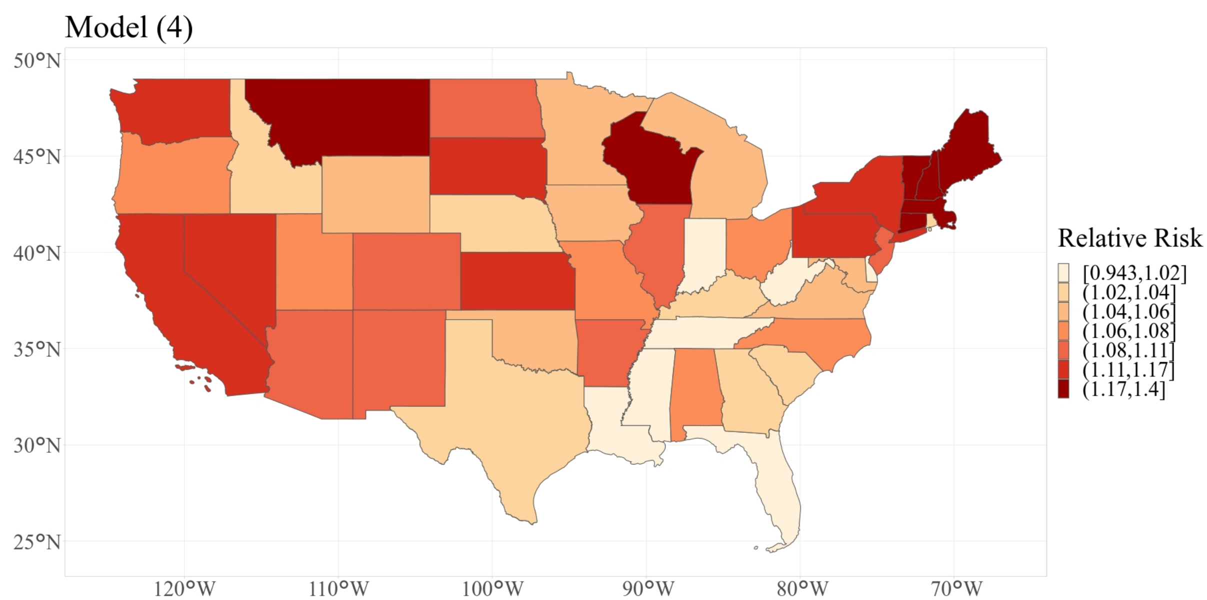
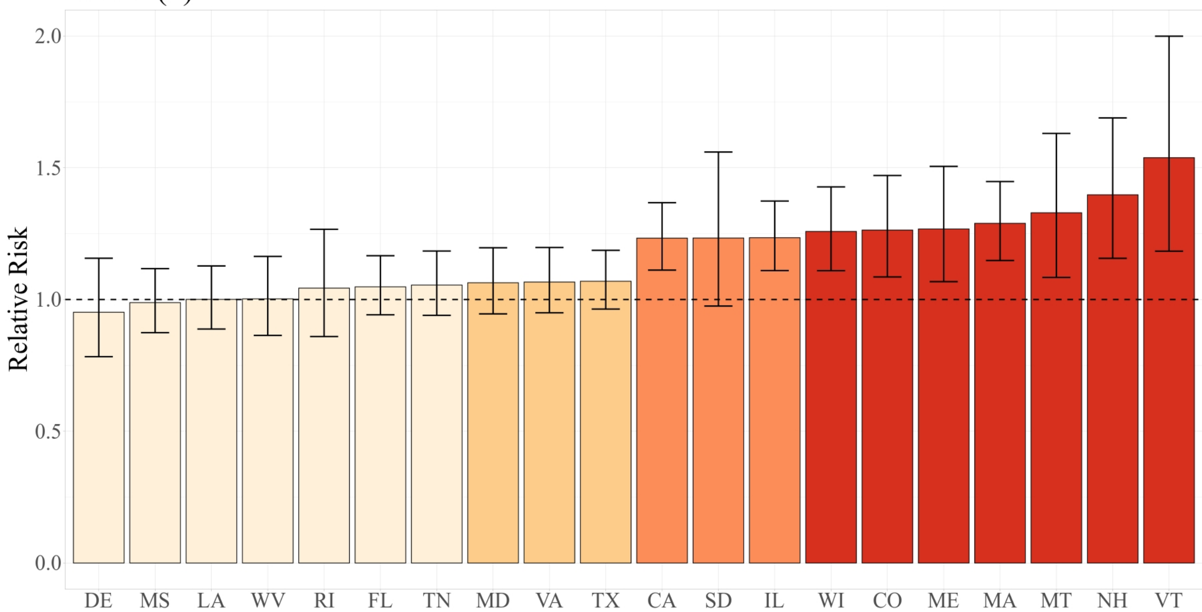


Figure 5.2.2: Relative Risk of Fluid and Electrolyte Hospitalization per State in the Contiguous U.S. from 2000-2016 Using a 95th Percentile Heat Index Threshold.

Model (3)



Model (4)

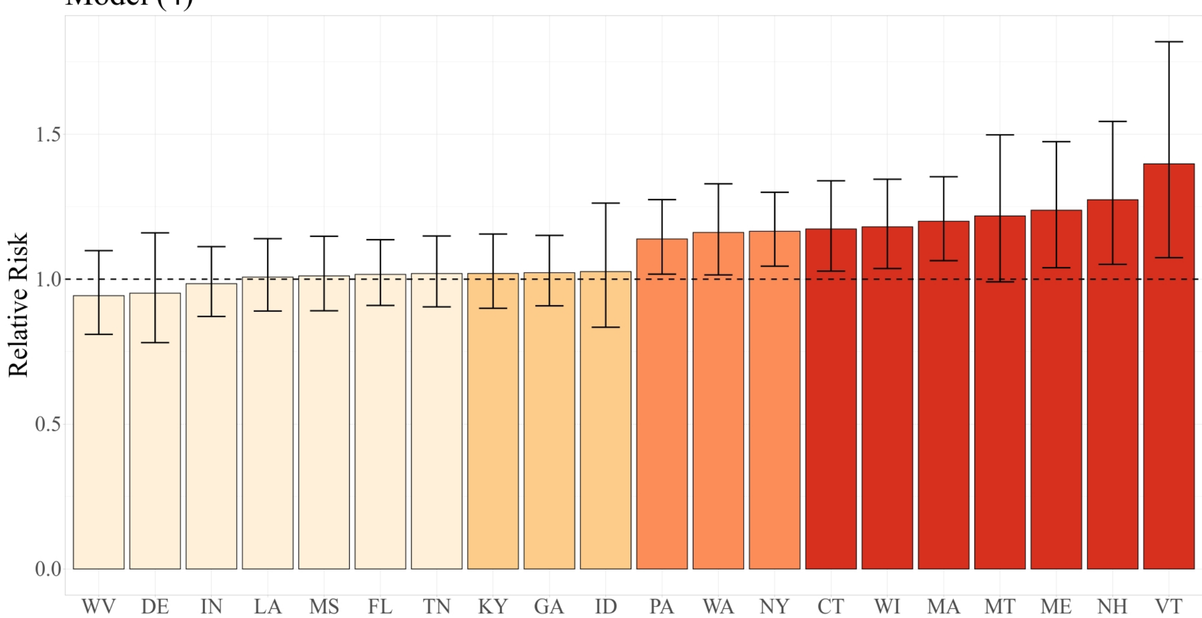


Figure 5.2.3: Top and Bottom Ten States with the Highest and Lowest Relative Risk of Fluid and Electrolyte Hospitalization in the Contiguous U.S. from 2000-2016 Using a 95th Percentile Heat Index Threshold.

icant evidence that certain states are notably *resilient* to heatwaves. Thus, being exposed to a heatwave is generally harmful across all states.

5.3 Sensitivity Analysis

As discussed previously, we conducted a sensitivity analysis to assess the robustness of our results relative to varying heat index thresholds. We chose a 95th percentile heat index threshold for our heatwave definition and a 97th percentile threshold for our sensitivity analysis, to ensure that either selection would not significantly change our results.

We recreated the EDA and modeling that we performed on the 95th percentile data on the 97th percentile data, and the full tables and figures are stored in the Appendix. Overall, our conclusions using the 95th percentile data remain mostly consistent using the 97th percentile data.

With respect to our model coefficients, the treatment coefficient is still positive across all four models. Models (1), (2), and (4) have similar treatment coefficient values to that of the models using the 95th percentile data, and the treatment coefficient for Model (3) is significantly higher, with a value of 0.214. It is worth noting that the treatment coefficient for Model (4) using the 97th percentile data was no longer statistically significant, but the coefficient for Models (1), (2), and (3) are all statistically significant at the $p < 0.001$ significance level. The main effects coefficients for our year and day of week variables again remain almost always significant across all models, with less statistical significance for the years 2003-2005.

With respect to our temporal analysis, Figure A.2.7 mirrors the conclusions we made using the 95th percentile data: the relative risk of fluid and electrolyte hospitalization has decreased over time on any day, but between the years of about 2003-2014, the relative risk was higher on heatwave days versus non-heatwave days. The coefficients of the interaction terms for Models (2) and (4) using the 97th percentile data also have greater magnitude when greater than 1, but have remained fairly constant overall.

With respect to our spatial analysis, based on Figure A.2.6, we see that, again, the Northeast, parts of the Midwest, and the West Coast have the highest relative risk values overall (some of which are even greater in magnitude than that of our primary analysis) and therefore exhibit the strongest vulnerability to heatwaves with respect to fluid and electrolyte hospitalizations. Using the 97th percentile data, we also see more vulnerability in the mid-Atlantic as opposed to the previous map. Again, parts of the South are not as vulnerable. Based on Figure A.2.7, Rhode Island, Washington DC, Massachusetts, Maine, New Hampshire, and Vermont have the highest relative risk of hospitalization.

5.4 Post-Hoc Vulnerability Analysis

After fitting our main models to determine the relationship between heatwave exposure and fluid and electrolyte hospitalizations over time and geographical area, we then sought to determine where additional factors of vulnerability and susceptibility to heatwaves might exist.

Considering that the effects of heatwaves are closely linked to one's access to air conditioning and cooler temperatures, we explored the association between the proportion of air conditioning (AC) prevalence per state and the relative risks (RR) of fluid and electrolyte hospitalization per state determined by our models. We produced two visualizations: (1) a heat-map of AC prevalence rates for each state and (2) a scatter plot of AC prevalence rates versus RR values across all states. The intent of these to plots is to be able to visually assess whether there is a relationship between AC prevalence and RR of hospitalization. We also considered modeling this relationship more formally through regression, but due to missing data in the AC dataset, we chose to only perform EDA.

First, we mapped the weighted-average air conditioning prevalence per state in the contiguous U.S. This map is intended to inform whether the states that had high relative risks of fluid and electrolyte hospitalization in Figure 5.2.2 also exhibit low air conditioning prevalence in Figure 5.4.1.

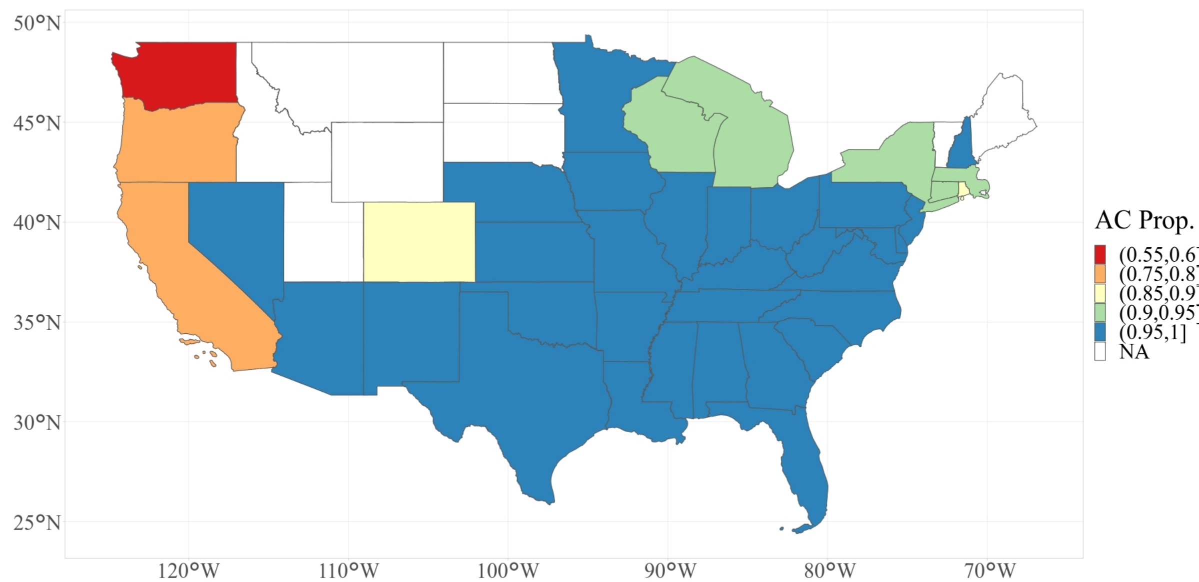


Figure 5.4.1: Air Conditioning Prevalence per State in the Contiguous U.S.

As seen in Figure 5.4.1, the West Coast, parts of the Midwest, and the Northeast have lower Air Condition prevalence than the rest of the contiguous U.S., with a notable number of states in the Midwest missing data overall. This follows our conclusions about the relative risk of hospitalizations, as the same regions also had the highest relative risk values. In addition, it is possible that there is an association between missing air conditioning data and air conditioning prevalence – in other words, perhaps locations missing AC data have a lower ground truth prevalence.

Next, we also plotted the relative risk values from Model (3) against the air conditioning prevalence values and fit a basic line of best fit to the data, as seen in Figure 5.4.2.

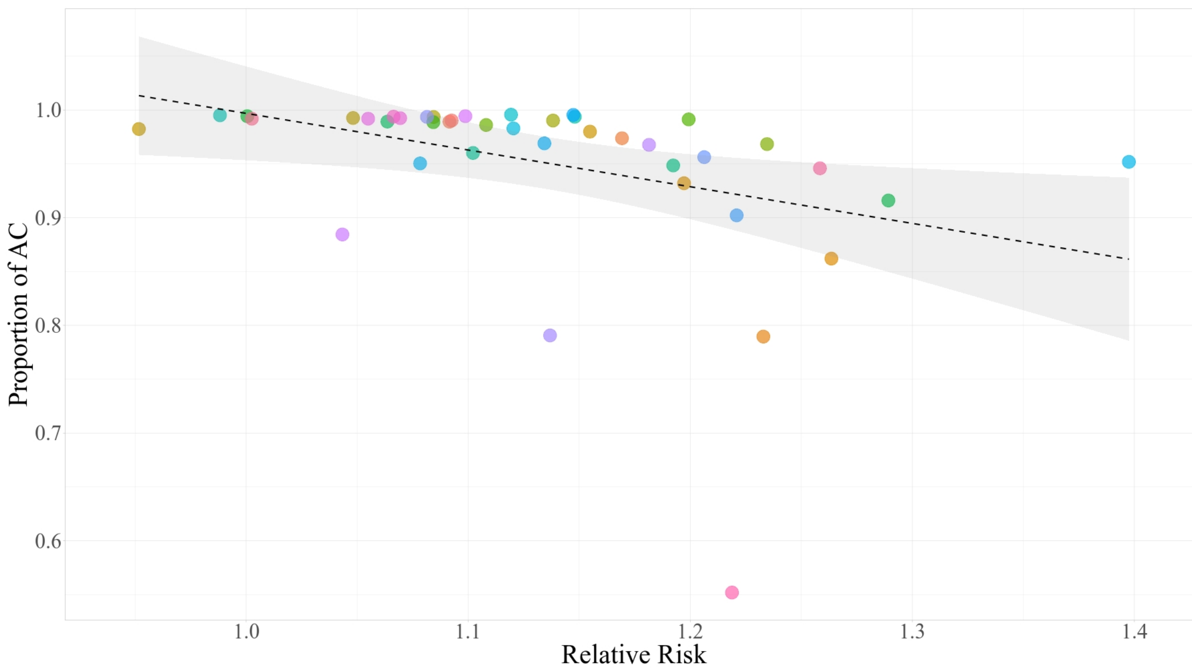


Figure 5.4.2: Scatterplot of Relative Risk of Fluid and Electrolyte Hospitalization from Model (3) (Using a 95th Percentile Heat Index Threshold) versus Air Conditioning Prevalence per State in the Contiguous U.S.

Figure 5.4.2 highlights that as the relative risk of fluid and electrolyte hospitalization on heatwave days versus non-heatwave days increases, the prevalence of air conditioning decreases.

Based on these two figures, we can conclude that there is evidence of an association between air conditioning prevalence and relative risk of fluid and electrolyte hospitalization on heatwave days versus non-heatwave days. This illustration underscores the need for additional research to explore effective state responses aimed at mitigating the adverse health effects of heatwaves.

6

Discussion

6.1 Summary of Main Findings

In replicating the model from Bobb et al 2014 [12] (titled Model (1)), we were able to confirm that the relative risk of fluid and electrolyte hospitalizations in the contiguous U.S. on a heatwave day versus a non-heatwave day is positive and statistically significant. This implies that Medicare enrollees are at a greater risk of fluid and electrolyte hospitalization during a heatwave than on a non-heatwave day. Thus, heatwaves have a statistically significant impact on people's health.

Our analysis not only confirmed the findings in Bobb et al 2014 but also extended them to account for temporal and spatial variability (Models (2), (3), and (4)). By modeling the interaction between heatwave exposure and year, we were able to conclude that there is a statistically significant relationship between the relative risk of fluid and electrolyte hospitalization and the year of the heatwave, and while the relative risk of hospitalization has decreased in general over time, there is still past evidence that heatwave days yield a higher risk than non-heatwave days (as exhibited by the constant interaction term between heatwave exposure and year).

In addition, we saw that the relative risk of fluid and electrolyte hospitalization varies notably across states in the contiguous U.S., with states in the Northeast, on the West Coast, and throughout the Midwest depicting the highest vulnerability to hospitalization. It is interesting to note that these areas with the greatest vulnerability tend to experience the greatest number of heatwave events, which are most often short in duration, while the less vulnerable areas (such as the South) experience fewer heatwaves of longer duration. California is particularly at risk, as it has both many heatwave events and heatwave days.

Furthermore, we found evidence that states with lower air conditioning prevalence (or no data on air conditioning at all) experienced greater relative risks of hospitalization, emphasizing the impact infrastructure has on people's health during periods of extreme heat.

6.2 Implications

In extending the Bobb et al 2014 analysis, we were able to make more specific conclusions about how vulnerability to heatwaves with respect to fluid and electrolyte hospitalizations varies over time and space.

While the conclusions of how vulnerability to heatwaves has changed over time is difficult to construct specific actions from, the spatial analysis we performed is highly actionable. Now that we know which states are more vulnerable than others, we can perform further analysis into the demographics and infrastructure of those areas to determine the most effective approaches to protecting vulnerable populations from the negative health impacts from heatwave exposure. Again, taking into consideration the increasing prevalence of climate change and its subsequent increases in temperature, it is exceedingly important to address these vulnerabilities sooner than later.

As demonstrated in our post-hoc vulnerability analyses, air conditioning is an infrastructural factor that relates to heat-related health vulnerability and could be a straightforward, immediately actionable step towards decreasing heat-related hospitalizations from heatwaves. Air conditioning prevalence could explain why states in the South experience a lower relative risk of fluid and electrolyte hospitalizations from a heatwave than the Northeast (which is notably lacking in robust air conditioning infrastructure), parts of the Midwest, and the West Coast.

One quick solution to keep people safe during heatwaves, that doesn't require systematic installation of air conditioning, is to implement cooling centers. According to a report by the CDC titled "The Use of Cooling Centers to Prevent Heat-Related Illness: Summary of Evidence and Strategies for Implementation" [18]:

> "*A cooling center (or "cooling shelter") is a location, typically an air-conditioned or cooled building that has been designated as a site to provide respite and safety during extreme heat. This may be a government-owned building such as a library or school, an existing community center, religious center, recreation center, or a private business such as a coffee shop, shopping mall, or movie theatre. Some counties have set up cooling sites outdoors in spray parks, community pools, and public parks. Sometimes temporary cool spaces are constructed for events such as a marathon or outdoor concert.*"

Therefore, the locations that lack highly prevalent air conditioning could benefit from the installation of cooling centers as a temporary solution during heatwaves, the implementation of which is detailed in the CDC's report. However, it is important to emphasize that since climate change will bring continuously rising temperatures, more robust infrastructure will be necessary. For example, we found that the most vulnerable areas with respect to fluid and electrolyte hospitalizations during heatwaves tend to experience a large quantity of heatwaves that are short in duration. This conclusion suggests that these areas would benefit more from systematic infrastructural changes, since heatwaves happen frequently enough to warrant long-lasting change.

In addition to infrastructural changes, it is immensely important to educate vulnerable populations on how to stay safe during heatwave events, such as staying hydrated, avoiding strenuous outdoor activity, or visiting a cooling center. Many health organizations have published informational packets and websites on how to stay safe during heatwaves, such as the American Red Cross [1], and local governments and new stations should thus disseminate this knowledge to their constituents, tailoring their advice based on the unique characteristics of their populations.

Overall, it is essential to consider that each geographic location has its own characteristics and needs, both with respect to the types of heatwaves they experience (frequent and short versus infrequent and long) and their individual population demographics. The purpose of our spatial analysis is to ensure that each location can understand their unique degree of vulnerability in order to tailor their responses appropriately in order to best keep their populations safe.

6.3 Limitations

Our study is subject to a few limitations based on the timeline, available data, and computational resources for our study.

First, based on the availability of Medicare enrollees and hospitalizations, the most recent data we were able to work with was from 2016. As a result, considering that it is now 2024, some of our conclusions may be outdated relative to the nature of heatwaves and fluid and electrolyte hospitalizations today. For example, we saw in Models (1) and (2) that fluid and electrolyte hospitalizations have decreased in general over time, so there is a chance that this hospitalization diagnosis may not be the best proxy for heat-related health impacts today. That being said, a lot of the previous work we based our research from is similarly limited in their recent availability of Medicare data, so we are on par with the literature on the relevancy of our analysis.

One major goal of our research was to understand the heterogeneity of heatwave vulnerability from a spatial context. At the very beginning of our research, we were working with ZIP code heat index and hospitalizations data, but we quickly found that if we wanted to apply our analysis on the entire contiguous U.S. at this granularity, we would require an extensive amount of computational resources for matching and model fitting. So, we instead created our matched data sets at the county (FIPS) level and were able to fit our models more quickly. However, when we fit our model that included the interaction between heatwave exposure and geographic location, the county-level data was still too computationally expensive. So, we opted to perform our spatial vulnerability analysis at the state level. In doing so, we eliminated some of the specificity of our analyses, which makes it difficult to suggest more targeted interventions to address heatwave vulnerability. However, we prioritized generalizability and coverage of the entire contiguous U.S. in our analysis as opposed to county or ZIP code level specificity, so we thus had to accept the trade-off of less granular results.

6.4 Future Work

Given more time and computational resources, our analyses could be performed with higher levels of granularity, either at the FIPS or ZIP code levels. The data already exists to perform these low-level analyses, they just require a lot of computational memory. The benefit of more granular analyses is that the results can inform more specific actions to best address each county or each ZIP code's unique demographics and infrastructure.

As mentioned in the Methods section, we opted to fit our models using fixed-effects over-dispersed conditional Poisson regression models due to computational constraints, but previous work (such as the original Bobb et al 2014 analysis) used mixed-effects regression models. These models are more computationally expensive but yield more precise results with respect to each geographical area. That being said, our fixed-effects models yielded similar coefficients to the mixed-effects one, so this extension may not be necessary even if more computational resources are made available.

A significant area of future work that we did not extensively explore is post-hoc vulnerability and heterogeneity analyses. For example, our post-hoc air conditioning EDA was fairly rudimentary, and we could bolster the conclusions we made with respect to AC prevalence and vulnerability to heatwaves using formal modeling techniques, such as including AC prevalence as a covariate in a regression model. In addition, we could explore the relationship between heatwave health impacts, AC prevalence, and race, as done in O'Neill et al 2005 [50]. In this paper, they find that the "*prevalence of central AC among Black households was less than half that among White households in all four cities, and deaths among Blacks were more strongly associated with hot temperatures. Central AC prevalence explained some of the differences in heat effects by race, but room-unit AC did not. Efforts to reduce disparities in heat-related mortality should consider access to AC*" (p.1)

In addition, going forward, we could utilize causal inference and machine learning techniques to uncover the most significant drivers of vulnerability given the availability of various demographic and geographic covariates (such as race, age, income, urbanicity, air pollution levels, etc). For example, we could leverage the novel Causal Rule Ensemble [6] to determine which covariates are significant drivers in heterogeneity with respect to fluid and electrolyte hospitalizations (by including interactions between these covariates and forming meaningful subgroups), then input those specific effect modifiers and subgroups into our regression models.

7
Conclusion

As discussed in the Introduction to our paper, the full scope of our research was to assess the relationship between heatwave exposure and fluid and electrolyte hospitalizations among Medicare enrollees in the United States from 2000-2016. A key aim was to identify which geographic regions in the U.S. are most vulnerable to this outcome to drive policy and infrastructural response to keep individuals safe during heatwaves.

Our analyses not only re-created existing work but also built upon previous models to generate more nuanced conclusions. For example, we performed temporal and spatial analyses on the relationship between fluid and electrolyte hospitalizations and heatwaves, and we yielded statistically significant results that give us insight into where heatwave vulnerability lies in the contiguous United States.

Our most significant finding is that the Northeast (e.g. Vermont, New Hampshire, Maine, Massachusetts, New York), West Coast (California, Washington), and parts of the Midwest (Montana, Colorado, Wisconsin) experienced the greatest relative risk to fluid and electrolyte hospitalizations during a heatwave from 2000-2016. These vulnerabilities may be driven by infrastructural shortcomings in these areas, such as a lack of air conditioning, which is an important weakness to note, as many of these vulnerable areas experience frequent heatwaves of short duration, making it a systematic issue.

Identifying which states across the contiguous U.S. are most vulnerable to heatwaves can help inform both local and nationwide policy and infrastructural response, such as the increased issuing of heat warnings, education of how to maintain one's physical health during a heatwave, and implementation of widespread air conditioning or as-needed cooling centers. Heatwaves affect individuals and locations differently, so it is of the utmost importance to identify where the variability in heatwave health impacts lies.

Climate change and global warming will continue to bring rising temperatures and extreme heat events. It is therefore important to know who to target first and how. Going forward, researchers can continue to narrow-in on who is most vulnerable to heatwaves, perhaps through causal inference and machine learning techniques to perform heterogeneous subgroup discovery with respect to various individual, ZIP code, and county-level demographics.

The effects of heatwaves are numerous and diverse, and while this research gives an initial insight into where certain populations particularly struggle, there is still more work to-do to keep the most vulnerable individuals and communities safe from extreme heat and its negative health impacts.

A

Appendix

A.1 Full Model Coefficients

Table A.1.1 is the full table of model coefficients for the two Bobb et al 2014 models fit in our main analysis using 95th percentile heat index threshold data.

Table A.1.1: Recreating Bobb et al 2014's Model with a Negative Binomial Model (`glmer.nb`) and Overdispersed Conditional Poisson Model (`gnm`) Using 95th Percentile Heat Index Data.

	Negative Binomial Model	Conditional Poisson Model
(Intercept)	-11.057^{***}	
	(0.013)	
Heatwave (Treatment)	0.086^{***}	0.087^{***}
	(0.004)	(0.004)
Tuesday	0.423^{***}	0.422^{***}
	(0.008)	(0.008)
Wednesday	0.388^{***}	0.388^{***}
	(0.008)	(0.008)
Thursday	0.333^{***}	0.333^{***}
	(0.008)	(0.008)
Friday	0.319^{***}	0.318^{***}
	(0.008)	(0.008)
Saturday	0.343^{***}	0.342^{***}
	(0.008)	(0.008)
Sunday	0.053^{***}	0.054^{***}
	(0.009)	(0.008)

	Negative Binomial Model	Conditional Poisson Model
2001	0.056***	0.056***
	(0.010)	(0.009)
2002	0.101***	0.104***
	(0.010)	(0.009)
2003	−0.017	−0.015
	(0.010)	(0.009)
2004	−0.091***	−0.090***
	(0.010)	(0.010)
2005	−0.132***	−0.130***
	(0.011)	(0.010)
2006	−0.229***	−0.225***
	(0.012)	(0.011)
2007	−0.240***	−0.238***
	(0.011)	(0.011)
2008	−0.295***	−0.291***
	(0.012)	(0.012)
2009	−0.321***	−0.318***
	(0.012)	(0.011)
2010	−0.350***	−0.346***
	(0.011)	(0.011)
2011	−0.466***	−0.462***
	(0.012)	(0.011)

	Negative Binomial Model	Conditional Poisson Model
2012	-0.569^{***}	-0.563^{***}
	(0.012)	(0.011)
2013	-0.699^{***}	-0.693^{***}
	(0.012)	(0.011)
2014	-0.767^{***}	-0.762^{***}
	(0.012)	(0.011)
2015	-0.751^{***}	-0.745^{***}
	(0.011)	(0.011)
2016	-0.861^{***}	-0.855^{***}
	(0.012)	(0.012)
Observations	1,559,956	1,559,956

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.1.2 is the full table of model coefficients for the four models fit in our main analysis using 95th percentile heat index threshold data.

Table A.1.2: Comparing Over-dispersed Conditional Poisson Models (1), (2), (3), (4) Using 95th Percentile Heat Index Data.

	Model			
	(1)	(2)	(3)	(4)
Heatwave (Treatment)	0.087***	0.081***	0.089***	0.073**
	(0.004)	(0.014)	(0.025)	(0.027)
2001	0.056***	0.039**		0.042**
	(0.009)	(0.013)		(0.013)
2002	0.104***	0.127***		0.123***
	(0.009)	(0.013)		(0.013)
2003	−0.015	−0.018		−0.015
	(0.009)	(0.013)		(0.012)
2004	−0.090***	−0.089***		−0.091***
	(0.010)	(0.014)		(0.014)
2005	−0.130***	−0.129***		−0.135***
	(0.010)	(0.016)		(0.016)
2006	−0.225***	−0.271***		−0.271***
	(0.011)	(0.019)		(0.019)
2007	−0.238***	−0.228***		−0.233***
	(0.011)	(0.017)		(0.017)

	(1)	(2)	(3)	(4)
2008	-0.291^{***}	-0.293^{***}		-0.293^{***}
	(0.012)	(0.019)		(0.019)
2009	-0.318^{***}	-0.333^{***}		-0.339^{***}
	(0.011)	(0.017)		(0.017)
2010	-0.346^{***}	-0.351^{***}		-0.351^{***}
	(0.011)	(0.016)		(0.016)
2011	-0.462^{***}	-0.506^{***}		-0.505^{***}
	(0.011)	(0.017)		(0.017)
2012	-0.563^{***}	-0.599^{***}		-0.596^{***}
	(0.011)	(0.016)		(0.016)
2013	-0.693^{***}	-0.721^{***}		-0.718^{***}
	(0.011)	(0.016)		(0.016)
2014	-0.762^{***}	-0.759^{***}		-0.756^{***}
	(0.011)	(0.015)		(0.015)
2015	-0.745^{***}	-0.735^{***}		-0.733^{***}
	(0.011)	(0.015)		(0.015)
2016	-0.855^{***}	-0.854^{***}		-0.850^{***}
	(0.012)	(0.015)		(0.015)
Tuesday	0.422^{***}			0.422^{***}
	(0.008)			(0.008)
Wednesday	0.388^{***}			0.387^{***}
	(0.008)			(0.008)

	(1)	(2)	(3)	(4)
Thursday	0.333***			0.333***
	(0.008)			(0.008)
Friday	0.318***			0.318***
	(0.008)			(0.008)
Saturday	0.342***			0.342***
	(0.008)			(0.008)
Sunday	0.054***			0.054***
	(0.008)			(0.008)
Heatwave:2001		0.040*		0.029
		(0.019)		(0.019)
Heatwave:2002		−0.048*		−0.035
		(0.019)		(0.019)
Heatwave:2003		0.009		−0.001
		(0.019)		(0.019)
Heatwave:2004		0.004		0.005
		(0.020)		(0.020)
Heatwave:2005		−0.004		0.007
		(0.021)		(0.021)
Heatwave:2006		0.068**		0.068**
		(0.024)		(0.024)
Heatwave:2007		0.003		−0.007
		(0.023)		(0.023)

	(1)	(2)	(3)	(4)
Heatwave:2008		−0.003		0.008
		(0.024)		(0.024)
Heatwave:2009		0.019		0.034
		(0.023)		(0.023)
Heatwave:2010		0.012		0.013
		(0.022)		(0.022)
Heatwave:2011		0.073**		0.075**
		(0.023)		(0.023)
Heatwave:2012		0.063**		0.063**
		(0.023)		(0.023)
Heatwave:2013		0.064**		0.054*
		(0.023)		(0.023)
Heatwave:2014		−0.007		−0.015
		(0.023)		(0.023)
Heatwave:2015		−0.032		−0.033
		(0.022)		(0.022)
Heatwave:2016		−0.018		−0.015
		(0.024)		(0.024)
Heatwave:AR			−0.001	0.010
			(0.041)	(0.040)
Heatwave:AZ			0.068	0.011
			(0.042)	(0.041)

	(1)	(2)	(3)	(4)
Heatwave:CA			0.121***	0.045
			(0.028)	(0.028)
Heatwave:CO			0.145**	0.019
			(0.053)	(0.052)
Heatwave:CT			0.091*	0.087*
			(0.041)	(0.040)
Heatwave:DC			0.055	0.003
			(0.077)	(0.075)
Heatwave:DE			−0.138	−0.122
			(0.075)	(0.073)
Heatwave:FL			−0.041	−0.056
			(0.030)	(0.029)
Heatwave:GA			−0.007	−0.050
			(0.034)	(0.033)
Heatwave:IA			0.041	−0.012
			(0.048)	(0.047)
Heatwave:ID			−0.017	−0.047
			(0.080)	(0.078)
Heatwave:IL			0.122***	0.029
			(0.030)	(0.029)
Heatwave:IN			0.014	−0.088*
			(0.036)	(0.035)

	(1)	(2)	(3)	(4)
Heatwave:KS			0.093*	0.031
			(0.045)	(0.044)
Heatwave:KY			−0.008	−0.053
			(0.037)	(0.036)
Heatwave:LA			−0.088*	−0.065
			(0.036)	(0.036)
Heatwave:MA			0.166***	0.110**
			(0.035)	(0.034)
Heatwave:MD			−0.027	−0.031
			(0.036)	(0.035)
Heatwave:ME			0.149*	0.141*
			(0.063)	(0.062)
Heatwave:MI			0.087**	−0.025
			(0.032)	(0.032)
Heatwave:MN			0.009	−0.034
			(0.046)	(0.045)
Heatwave:MO			0.050	0.004
			(0.035)	(0.034)
Heatwave:MS			−0.100**	−0.061
			(0.038)	(0.037)
Heatwave:MT			0.196*	0.125
			(0.080)	(0.078)

	(1)	(2)	(3)	(4)
Heatwave:NC			0.024	−0.004
			(0.033)	(0.032)
Heatwave:ND			0.056	0.021
			(0.101)	(0.099)
Heatwave:NE			0.025	−0.036
			(0.065)	(0.063)
Heatwave:NH			0.246**	0.170*
			(0.072)	(0.071)
Heatwave:NJ			−0.013	0.014
			(0.032)	(0.031)
Heatwave:NM			0.038	0.010
			(0.060)	(0.059)
Heatwave:NV			0.049	0.054
			(0.059)	(0.058)
Heatwave:NY			0.111***	0.080**
			(0.029)	(0.028)
Heatwave:OH			0.099**	−0.010
			(0.032)	(0.031)
Heatwave:OK			−0.010	−0.032
			(0.038)	(0.037)
Heatwave:OR			0.040	−0.006
			(0.057)	(0.056)

	(1)	(2)	(3)	(4)
Heatwave:PA			0.078*	0.057
			(0.031)	(0.030)
Heatwave:RI			−0.046	−0.042
			(0.074)	(0.073)
Heatwave:SC			0.006	−0.036
			(0.036)	(0.036)
Heatwave:SD			0.121	0.055
			(0.095)	(0.093)
Heatwave:TN			−0.035	−0.053
			(0.034)	(0.034)
Heatwave:TX			−0.021	−0.039
			(0.029)	(0.028)
Heatwave:UT			0.063	0.000
			(0.067)	(0.065)
Heatwave:VA			−0.024	−0.034
			(0.035)	(0.034)
Heatwave:VT			0.342**	0.262*
			(0.109)	(0.107)
Heatwave:WA			0.109*	0.077
			(0.042)	(0.041)
Heatwave:WI			0.141***	0.094*
			(0.040)	(0.039)

	(1)	(2)	(3)	(4)
Heatwave:WV			-0.086	-0.131^{**}
			(0.051)	(0.050)
Heatwave:WY			0.076	-0.022
			(0.097)	(0.095)
Observations	1,559,956	1,559,956	1,559,956	1,559,956

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

A.2 Sensitivity Analysis Results

In this section, we provide the same figures and tables from the Data and Results sections that we generated on the 95th percentile matched data set but instead on the 97th percentile matched data set, as our sensitivity analysis.

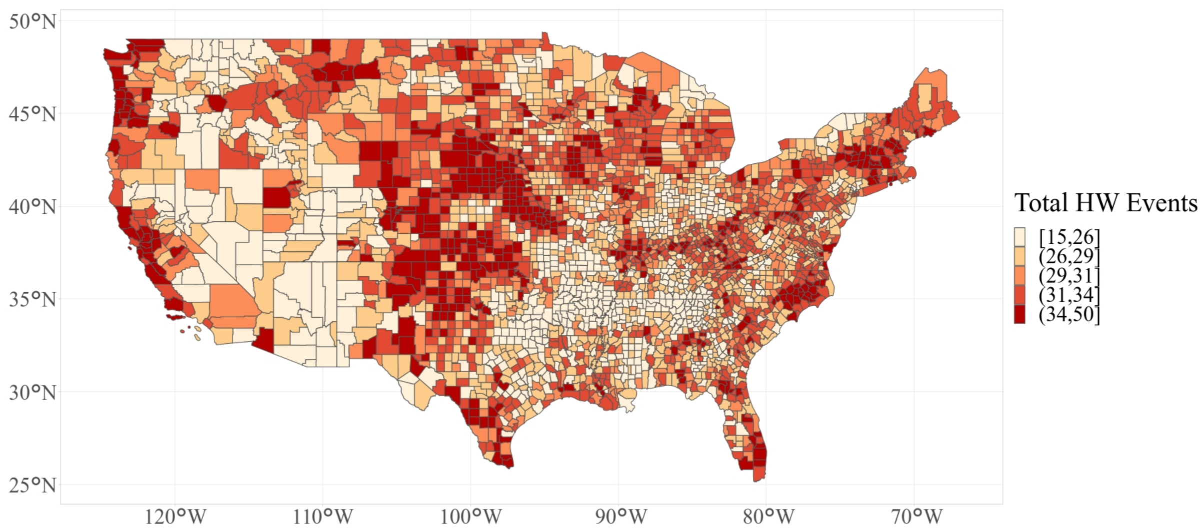


Figure A.2.1: Total Heatwave Events per County from 2000-2016 in the Contiguous U.S. Using a 97th Percentile Heat Index Threshold.

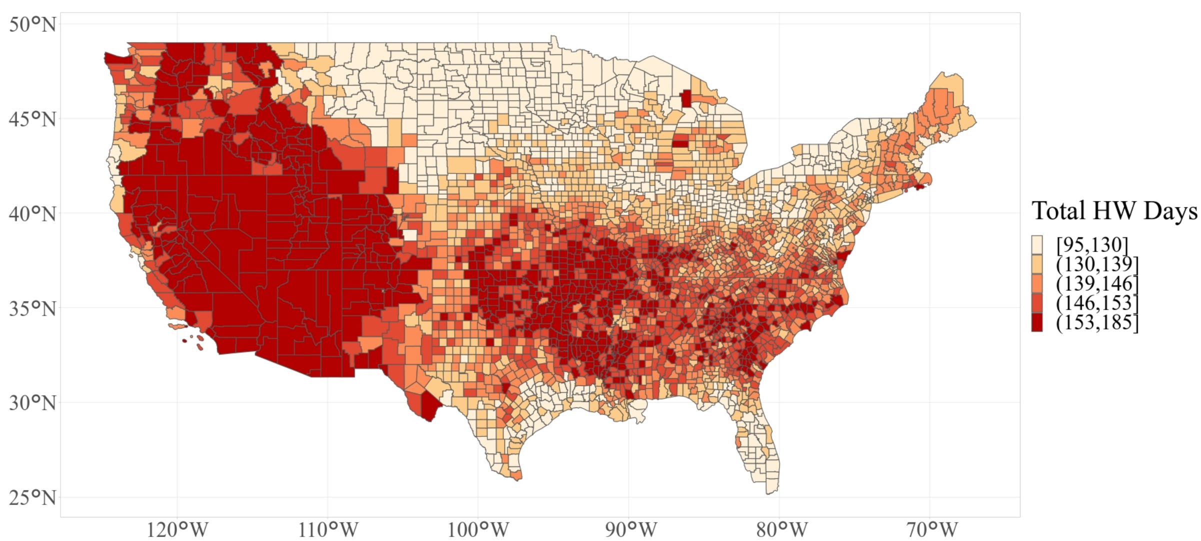


Figure A.2.2: Total Heatwave Days per County from 2000-2016 in the Contiguous U.S. Using a 97th Percentile Heat Index Threshold.

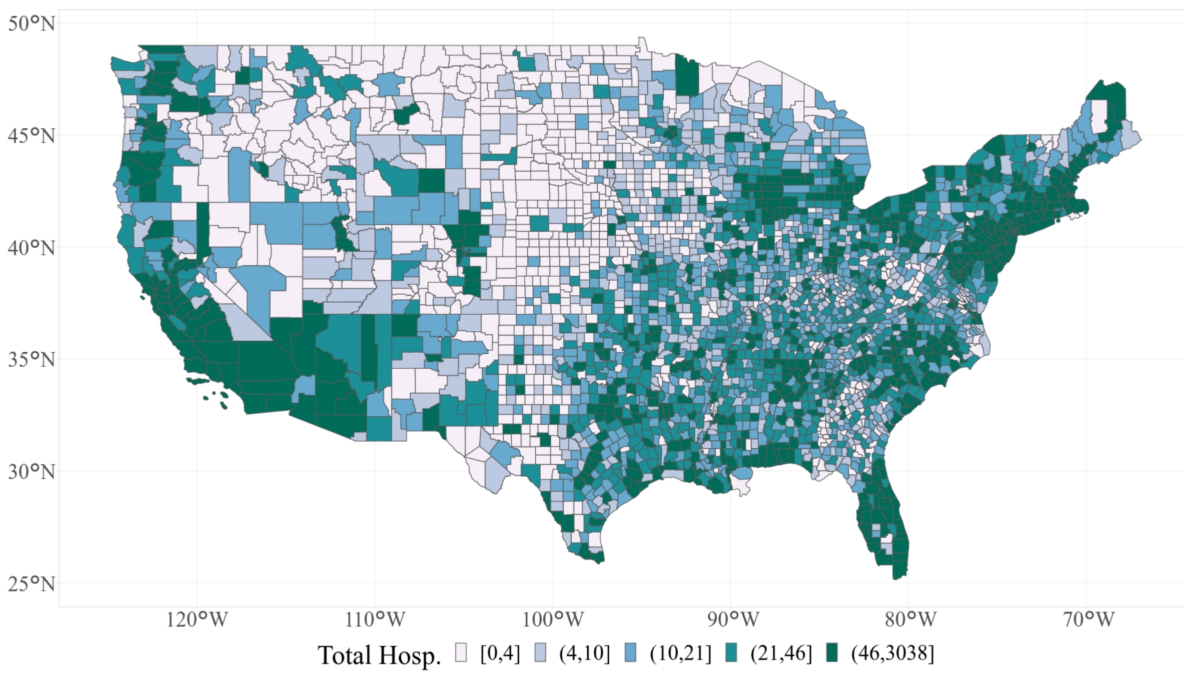


Figure A.2.3: Total Fluid and Electrolyte Hospitalizations from 2000-2016 among Medicare Enrollees in the Contiguous U.S. Using a 97th Percentile Heat Index Threshold.

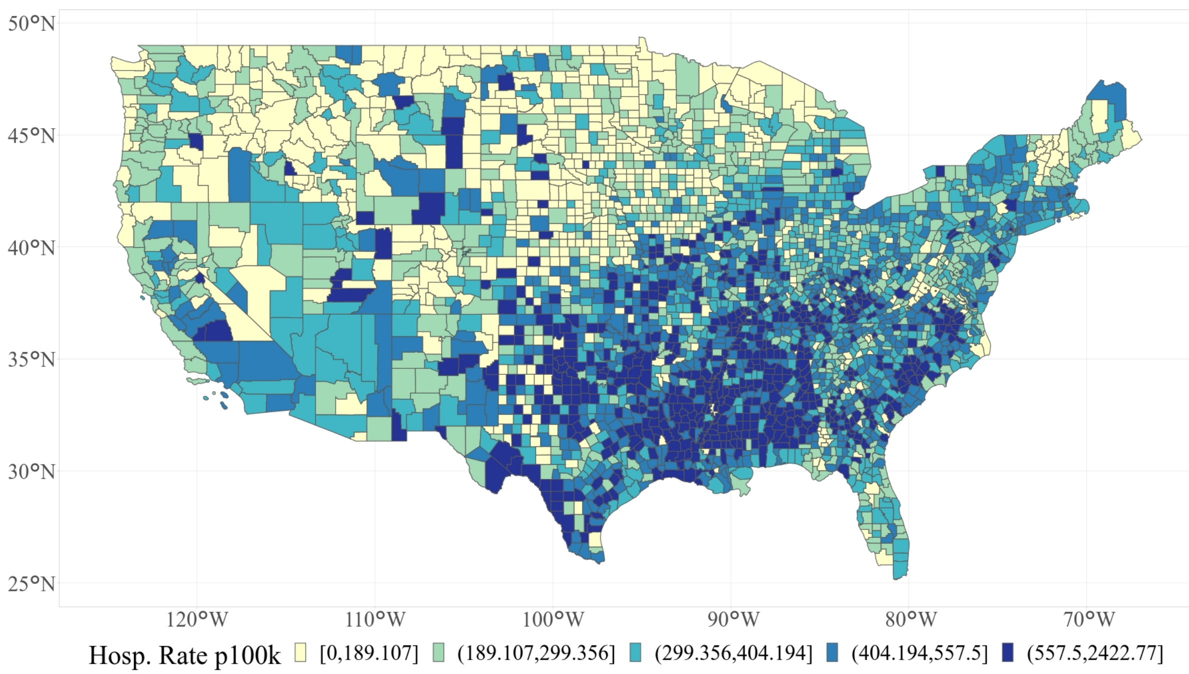


Figure A.2.4: Total Fluid and Electrolyte Hospitalizations per 100k Medicare Enrollees from 2000-2016 in the Contiguous U.S. Using a 97th Percentile Heat Index Threshold.

Table A.2.1: Recreating Bobb et al 2014's Model with a Negative Binomial Model (`glmer.nb`) and Overdispersed Conditional Poisson Model (`gnm`) Using 97th Percentile Heat Index Data.

	Negative Binomial Model	Conditional Poisson Model
(Intercept)	-11.019^{***}	
	(0.016)	
Heatwave (Treatment)	0.090^{***}	0.091^{***}
	(0.006)	(0.006)
Tuesday	0.416^{***}	0.42^{***}
	(0.011)	(0.011)
Wednesday	0.380^{***}	0.38^{***}
	(0.011)	(0.011)
Thursday	0.334^{***}	0.33^{***}
	(0.011)	(0.011)
Friday	0.311^{***}	0.31^{***}
	(0.012)	(0.011)
Saturday	0.346^{***}	0.34^{***}
	(0.012)	(0.011)
Sunday	0.055^{***}	0.05^{***}
	(0.012)	(0.012)
2001	0.073^{***}	0.075^{***}
	(0.015)	(0.014)
2002	0.078^{***}	0.079^{***}
	(0.015)	(0.014)

	Negative Binomial Model	Conditional Poisson Model
2003	-0.033^{*}	-0.028
	(0.015)	(0.015)
2004	-0.102^{***}	-0.096^{***}
	(0.018)	(0.017)
2005	-0.151^{***}	-0.146^{***}
	(0.017)	(0.016)
2006	-0.197^{***}	-0.190^{***}
	(0.017)	(0.016)
2007	-0.267^{***}	-0.262^{***}
	(0.017)	(0.016)
2008	-0.310^{***}	-0.305^{***}
	(0.018)	(0.018)
2009	-0.341^{***}	-0.336^{***}
	(0.017)	(0.016)
2010	-0.379^{***}	-0.374^{***}
	(0.015)	(0.015)
2011	-0.475^{***}	-0.468^{***}
	(0.015)	(0.014)
2012	-0.589^{***}	-0.581^{***}
	(0.015)	(0.015)
2013	-0.701^{***}	-0.693^{***}
	(0.015)	(0.015)

	Negative Binomial Model	Conditional Poisson Model
2014	-0.804^{***}	-0.799^{***}
	(0.015)	(0.015)
2015	-0.774^{***}	-0.767^{***}
	(0.016)	(0.015)
2016	-0.859^{***}	-0.852^{***}
	(0.017)	(0.016)
Observations	823,708	823,708

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.2.2: Comparing Over-dispersed Conditional Poisson Models (1), (2), (3), (4) Using 97th Percentile Heat Index Data.

	Model			
	(1)	(2)	(3)	(4)
Heatwave (Treatment)	0.091***	0.071***	0.214***	0.069
	(0.006)	(0.020)	(0.034)	(0.039)
2001	0.075***	0.071**		0.072**
	(0.014)	(0.023)		(0.023)
2002	0.079***	0.094***		0.096***
	(0.014)	(0.023)		(0.023)
2003	−0.028	−0.042		−0.032
	(0.015)	(0.024)		(0.024)
2004	−0.096***	−0.015		−0.016
	(0.017)	(0.042)		(0.042)
2005	−0.146***	−0.109*		−0.113*
	(0.016)	(0.045)		(0.045)
2006	−0.190***	−0.250***		−0.255***
	(0.016)	(0.046)		(0.046)
2007	−0.262***	−0.299***		−0.287***
	(0.016)	(0.035)		(0.035)
2008	−0.305***	−0.276***		−0.267***
	(0.018)	(0.040)		(0.040)
2009	−0.336***	−0.403***		−0.382***

	(1)	(2)	(3)	(4)
	(0.016)	(0.027)		(0.027)
2010	-0.374^{***}	-0.377^{***}		-0.376^{***}
	(0.015)	(0.021)		(0.021)
2011	-0.468^{***}	-0.500^{***}		-0.492^{***}
	(0.014)	(0.020)		(0.020)
2012	-0.581^{***}	-0.622^{***}		-0.605^{***}
	(0.015)	(0.020)		(0.020)
2013	-0.693^{***}	-0.727^{***}		-0.710^{***}
	(0.015)	(0.020)		(0.020)
2014	-0.799^{***}	-0.814^{***}		-0.794^{***}
	(0.015)	(0.019)		(0.019)
2015	-0.767^{***}	-0.762^{***}		-0.749^{***}
	(0.015)	(0.020)		(0.020)
2016	-0.852^{***}	-0.850^{***}		-0.833^{***}
	(0.016)	(0.021)		(0.021)
Tuesday	0.415^{***}			0.415^{***}
	(0.011)			(0.011)
Wednesday	0.380^{***}			0.378^{***}
	(0.011)			(0.011)
Thursday	0.333^{***}			0.331^{***}
	(0.011)			(0.011)
Friday	0.308^{***}			0.306^{***}

	(1)	(2)	(3)	(4)
	(0.011)			(0.011)
Saturday	0.344***			0.342***
	(0.011)			(0.011)
Sunday	0.055***			0.054***
	(0.012)			(0.012)
Heatwave:2001		0.026		0.006
		(0.029)		(0.029)
Heatwave:2002		−0.028		−0.023
		(0.030)		(0.030)
Heatwave:2003		0.046		0.010
		(0.031)		(0.031)
Heatwave:2004		−0.070		−0.082
		(0.046)		(0.046)
Heatwave:2005		−0.039		−0.030
		(0.049)		(0.049)
Heatwave:2006		0.089		0.077
		(0.050)		(0.050)
Heatwave:2007		0.082*		0.038
		(0.040)		(0.040)
Heatwave:2008		−0.037		−0.039
		(0.045)		(0.045)
Heatwave:2009		0.085*		0.070*

	(1)	(2)	(3)	(4)
		(0.034)		(0.034)
Heatwave:2010		0.014		0.008
		(0.030)		(0.030)
Heatwave:2011		0.067*		0.057
		(0.029)		(0.029)
Heatwave:2012		0.092		0.073*
		(0.030)		(0.030)
Heatwave:2013		0.076*		0.049
		(0.030)		(0.030)
Heatwave:2014		0.020		−0.004
		(0.031)		(0.031)
Heatwave:2015		−0.026		−0.045
		(0.031)		(0.031)
Heatwave:2016		−0.037		−0.043
		(0.033)		(0.033)
Heatwave:AR			−0.023	0.078
			(0.056)	(0.055)
Heatwave:AZ			−0.013	0.021
			(0.057)	(0.056)
Heatwave:CA			0.161***	0.062
			(0.039)	(0.039)
Heatwave:CO			−0.071	0.006

	(1)	(2)	(3)	(4)
			(0.069)	(0.068)
Heatwave:CT			0.155**	−0.047
			(0.058)	(0.057)
Heatwave:DC			0.379**	0.215
			(0.116)	(0.114)
Heatwave:DE			0.097	−0.005
			(0.111)	(0.109)
Heatwave:FL			−0.016	−0.146***
			(0.042)	(0.042)
Heatwave:GA			0.041	−0.015
			(0.047)	(0.046)
Heatwave:IA			0.059	0.026
			(0.069)	(0.068)
Heatwave:ID			−0.056	0.011
			(0.107)	(0.105)
Heatwave:IL			0.098*	0.053
			(0.042)	(0.041)
Heatwave:IN			−0.068	−0.095
			(0.049)	(0.049)
Heatwave:KS			−0.062	0.014
			(0.061)	(0.060)
Heatwave:KY			0.068	0.002

	(1)	(2)	(3)	(4)
			(0.052)	(0.051)
Heatwave:LA			-0.155^{**}	-0.077
			(0.051)	(0.050)
Heatwave:MA			0.408^{***}	0.200^{***}
			(0.049)	(0.049)
Heatwave:MD			0.236^{***}	0.063
			(0.052)	(0.051)
Heatwave:ME			0.514^{***}	0.264^{**}
			(0.095)	(0.093)
Heatwave:MI			0.078	-0.083
			(0.045)	(0.044)
Heatwave:MN			0.025	-0.026
			(0.067)	(0.066)
Heatwave:MO			0.027	0.049
			(0.049)	(0.048)
Heatwave:MS			-0.126^{*}	-0.077
			(0.053)	(0.052)
Heatwave:MT			0.192	0.229^{*}
			(0.110)	(0.108)
Heatwave:NC			0.140^{**}	0.036
			(0.046)	(0.045)
Heatwave:ND			0.032	-0.080

	(1)	(2)	(3)	(4)
			(0.148)	(0.145)
Heatwave:NE			−0.101	−0.020
			(0.088)	(0.087)
Heatwave:NH			0.617***	0.339**
			(0.106)	(0.104)
Heatwave:NJ			0.245***	0.071
			(0.045)	(0.045)
Heatwave:NM			−0.008	−0.000
			(0.083)	(0.081)
Heatwave:NV			0.001	0.041
			(0.078)	(0.077)
Heatwave:NY			0.296***	0.065
			(0.041)	(0.040)
Heatwave:OH			0.136**	−0.006
			(0.045)	(0.044)
Heatwave:OK			−0.110*	−0.019
			(0.052)	(0.051)
Heatwave:OR			0.083	0.088
			(0.078)	(0.077)
Heatwave:PA			0.252***	0.082
			(0.044)	(0.043)
Heatwave:RI			0.332**	0.122

	(1)	(2)	(3)	(4)
			(0.113)	(0.111)
Heatwave:SC			0.078	0.007
			(0.051)	(0.050)
Heatwave:SD			−0.095	−0.040
			(0.128)	(0.126)
Heatwave:TN			0.096*	0.004
			(0.049)	(0.048)
Heatwave:TX			−0.102	−0.062
			(0.040)	(0.039)
Heatwave:UT			0.018	0.105
			(0.085)	(0.084)
Heatwave:VA			0.070	−0.067
			(0.049)	(0.048)
Heatwave:VT			0.735***	0.476**
			(0.158)	(0.155)
Heatwave:WA			0.010	0.053
			(0.058)	(0.056)
Heatwave:WI			0.173**	0.121*
			(0.056)	(0.055)
Heatwave:WV			0.023	−0.105
			(0.074)	(0.072)
Heatwave:WY			−0.097	−0.075

	(1)	(2)	(3)	(4)
			(0.122)	(0.119)
Observations	823,708	823,708	823,708	823,708

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

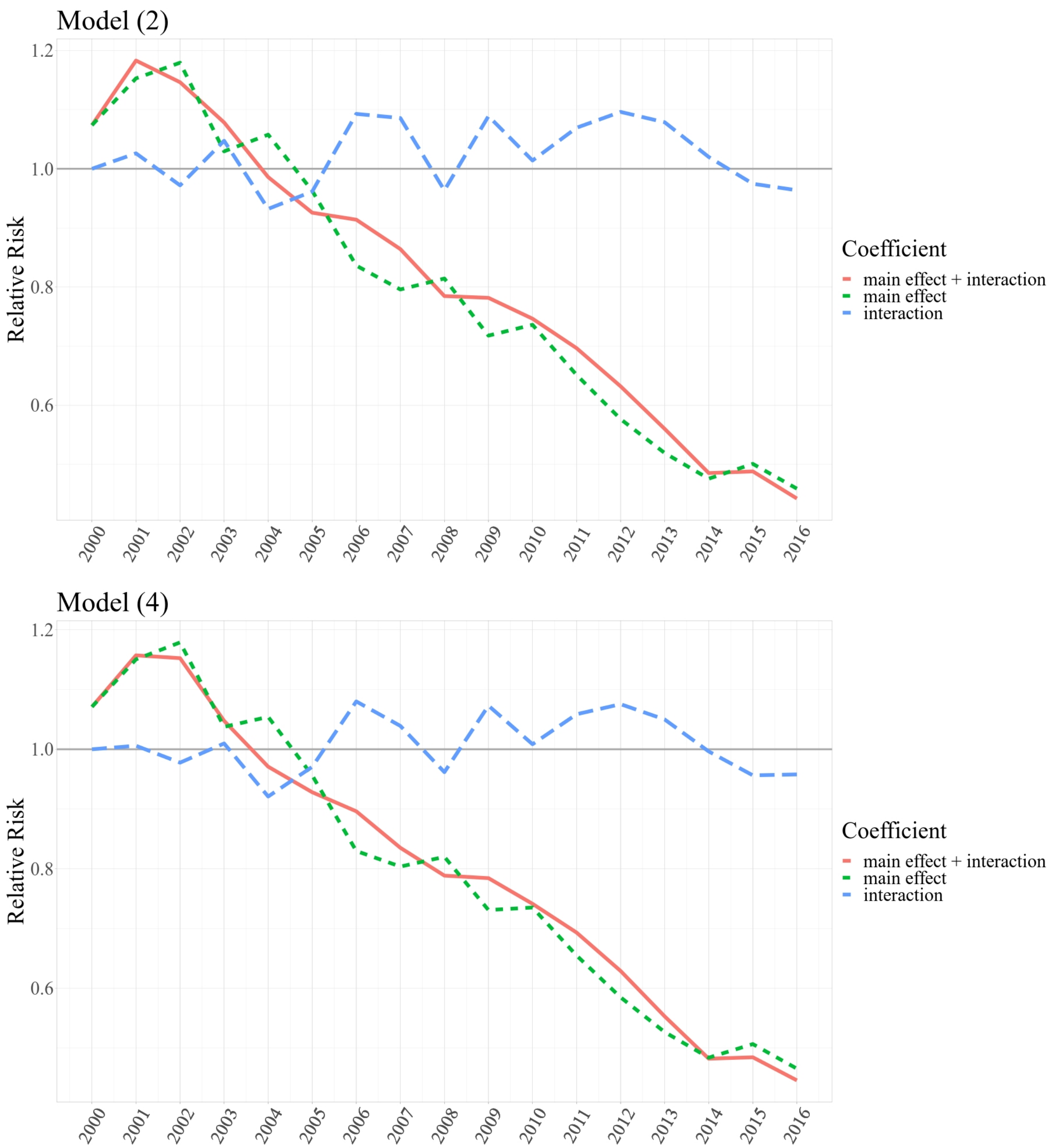


Figure A.2.5: Relative Risk of Fluid and Electrolyte Hospitalization Over Time from 2000-2016 in the Contiguous U.S., both Controlling and Not Controlling for a Heatwave Day Using a 97th Percentile Heat Index Threshold.

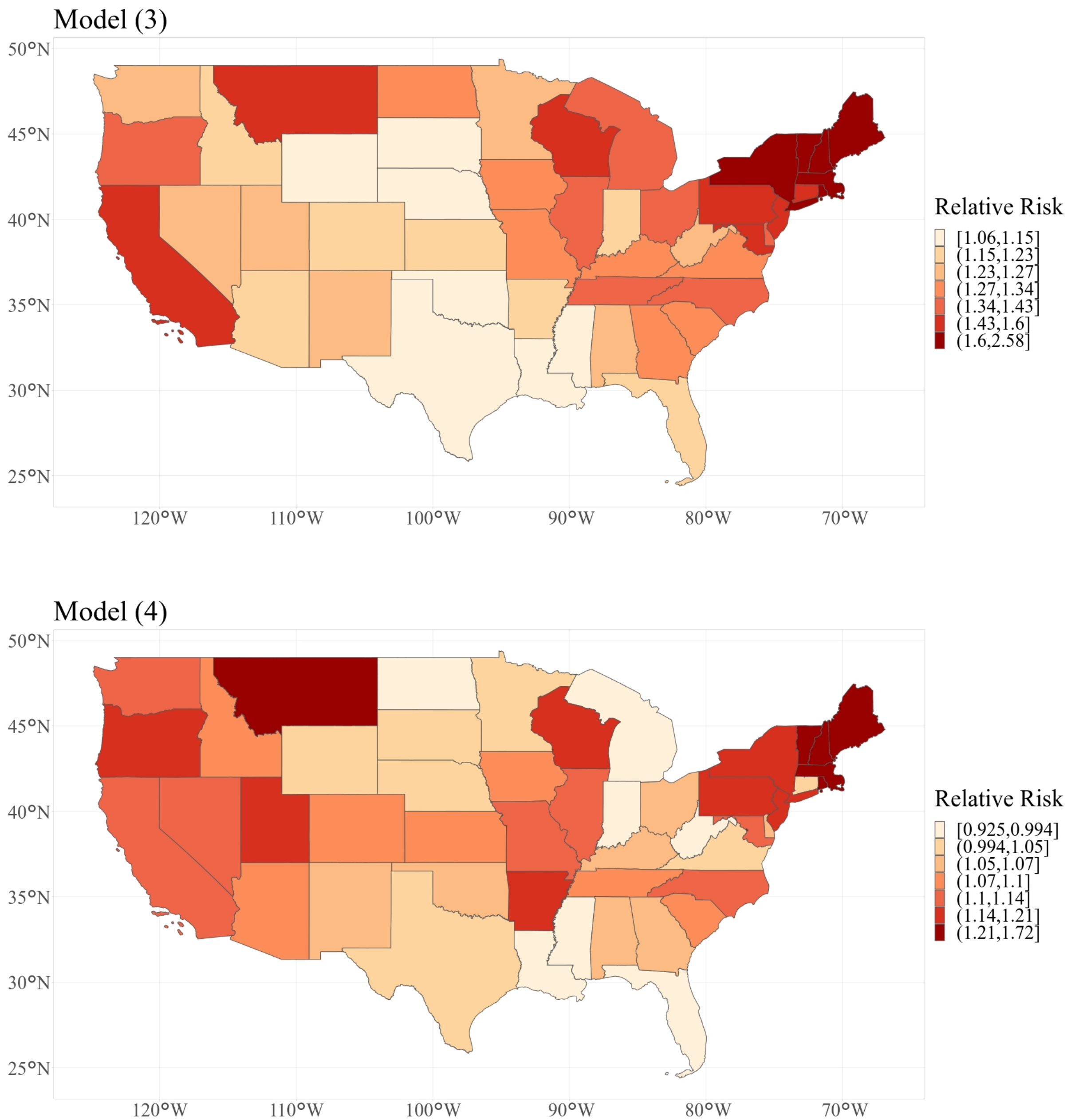


Figure A.2.6: Relative Risk of Fluid and Electrolyte Hospitalization per State in the Contiguous U.S. from 2000-2016 Using a 97th Percentile Heat Index Threshold.

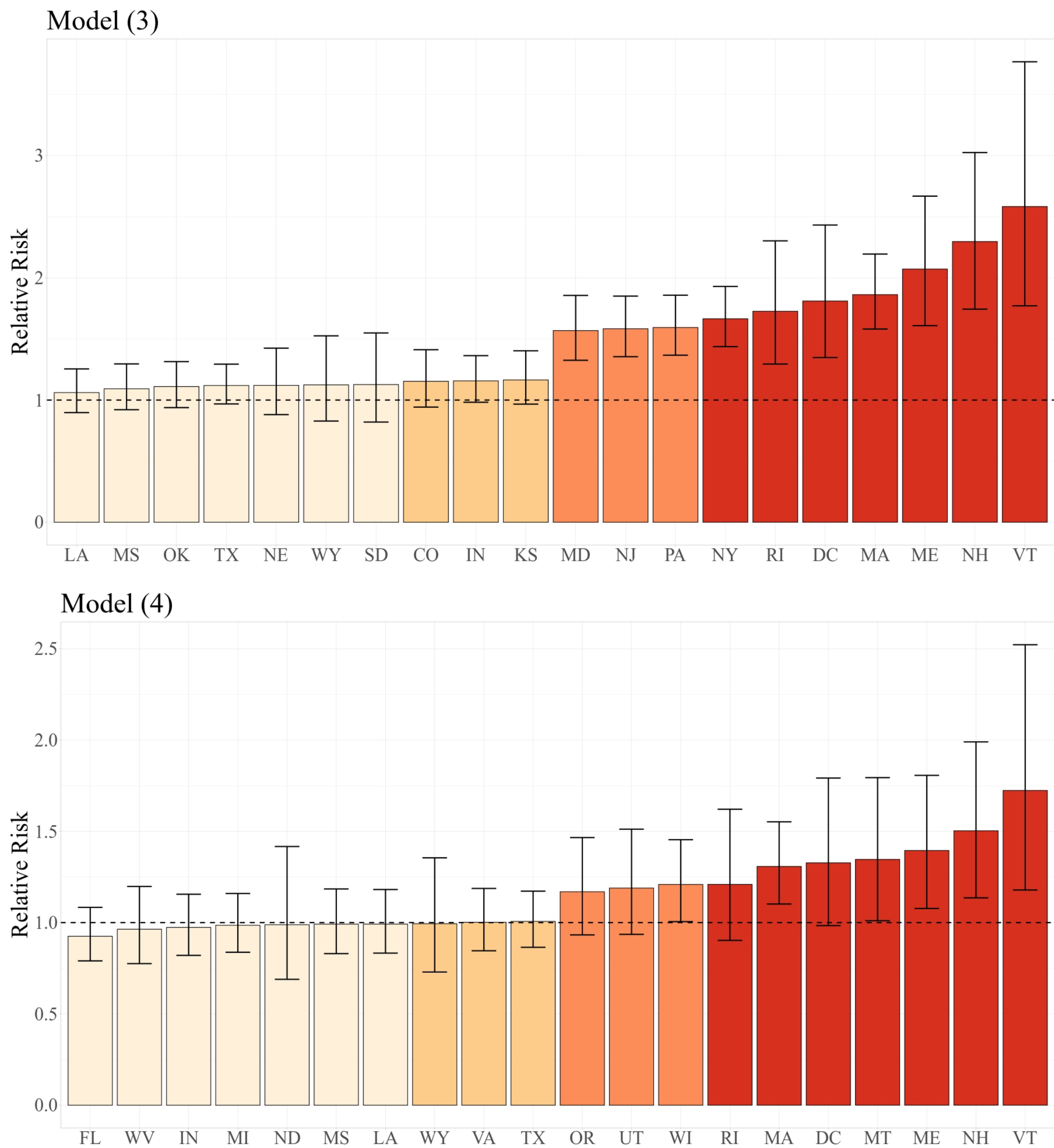


Figure A.2.7: Top and Bottom Ten States with the Highest and Lowest Relative Risk of Fluid and Electrolyte Hospitalization in the Contiguous U.S. from 2000-2016 Using a 97th Percentile Heat Index Threshold.

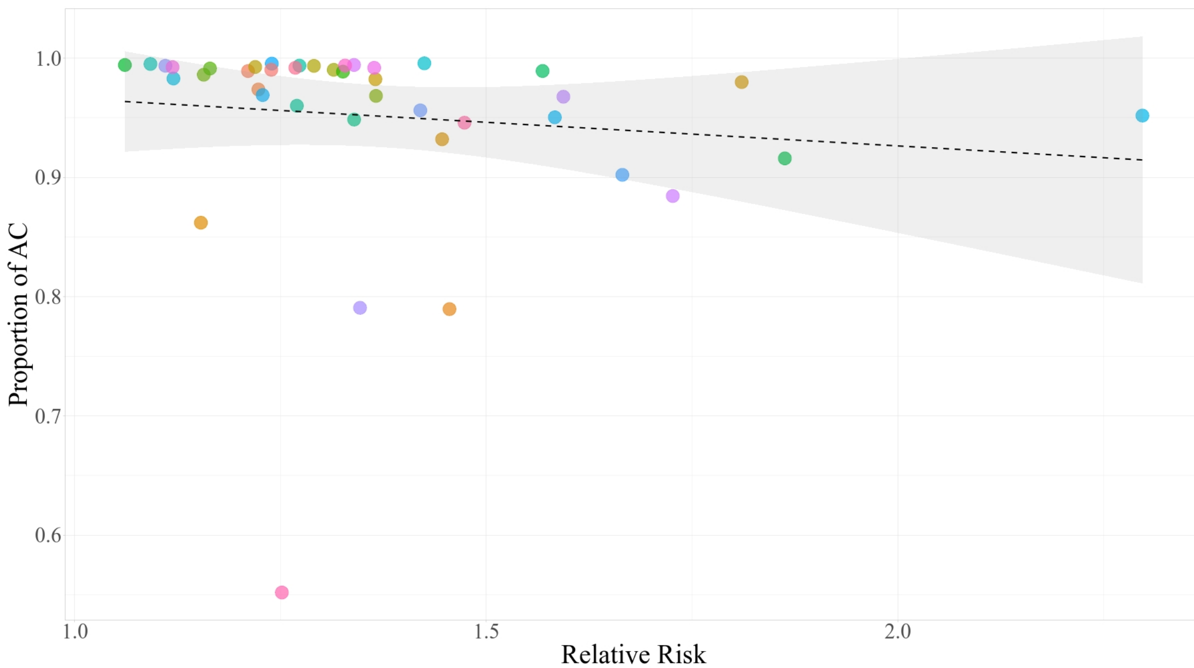


Figure A.2.8: Scatterplot of Relative Risk of Fluid and Electrolyte Hospitalization from Model (3) (Using a 97th Percentile Heat Index Threshold) versus Air Conditioning Prevalence per State in the Contiguous U.S.

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