SUMMER HEAT, HOSPITAL ADMISSIONS AND MORTALITY AMONG THE ELDERLY IN MICHIGAN AND THE UNITED STATES

by

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ABSTRACT

Background: With climate change and population aging, the health burden of extreme heat (EH) is a present and future concern. However, characteristics of vulnerability to EH and associations between EH and morbidity vs. mortality are not well understood, and previous studies have focused on small numbers of cities and/or used sociodemographic and land cover information at a course geographic resolution (e.g., city-level).

Objectives: For ages 65 and over, we examined 1) vulnerability to EH-associated mortality in 8 Michigan cities by individual and neighborhood socio-demographic characteristics and green space, 2) associations between heat and HAs in over 100 U.S. cities and 3) vulnerability to EH-associated HAs by individual and neighborhood characteristics and citywide air-conditioning prevalence in over 100 U.S. cities.

Methods: In time-stratified case-crossover designs, we regressed natural-cause mortality or HAs against moderate heat and EH, or an indicator for maximum or apparent temperature above a city-specific threshold, over multiple lag days. We examined vulnerability by personal and ZIP-code (neighborhood) characteristics using multiple interaction terms between each of the characteristics and EH terms and by citywide air-conditioning prevalence in meta-analyses.

Results: In Michigan, we observed increased vulnerability to heat-associated mortality among men, blacks and the very old (78 years or older). Nationally, EH was associated with higher HAs for cardiovascular, renal and respiratory diseases, with rates increasing by 43% (95% CI: 37%, 50%) for renal diseases, though over longer lags, substantial displacement of the initial effect

was observed for cardiovascular and respiratory HAs. We observed increased vulnerability to EH-associated HAs among men and the very old, in neighborhoods with more residents of nonwhite race and lower education and in cities with lower air-conditioning prevalence. Significant heterogeneity existed between cities for many of the vulnerability characteristics. Results were suggestive of increased vulnerability to heat-associated mortality and HAs in neighborhoods with less green space.

Conclusions: Individuals with respiratory and renal conditions may benefit from heat adaptation interventions, and heat health warning systems and vulnerability maps may benefit from incorporating information on heat-associated HAs. Socio-demographic characteristics and possibly green space modify the association between EH and HAs and mortality, though effects vary by city.

CHAPTER I

Dissertation Introduction

In the United States, heat is one of the deadliest natural hazards. More deaths are attributed directly to heat than to lightning, hurricanes, tornadoes or earthquakes (2005). Heat waves, extended periods of unusually high temperatures, can be especially deadly, even in the United States where many homes and public spaces are air-conditioned. During the week-long July, 1995 heat wave in Chicago, IL, the Cook County Medical Examiner's Office quickly exceeded its storage capacity and enlisted the help of a local meat-packing firm, which loaned the city nine 48-foot long refrigerated trucks to contain the hundreds of additional corpses (Klinenberg 2002). Some have questioned whether heat waves are truly a public health crisis, proposing that individuals who die due to heat, particularly the elderly, would have died due to other causes within a matter of days anyway (a phenomenon known as mortality displacement, or "harvesting.") (Schwartz et al. 2004). However, the death toll due to the Chicago 1995 heat wave has been estimated at 500 deaths, even after accounting for an estimated mortality displacement of 26% (Kaiser et al. 2007). Heat waves can be devastating in other industrialized nations, as well, as evidenced by the European heat wave of 2003, to which 35,000 excess deaths have been attributed (Kosatsky 2005). With global warming, heat waves are expected to increase in frequency, intensity and duration (Meehl and Tebaldi 2004) and could therefore become deadlier without a better understanding of whom they affect and of the actions required to protect the vulnerable.

The association between temperature and mortality is well known, and by the early 1990s, there was a renewed interest in this research with respect to climate change (Gosling et al. 2009). Many studies have improved our understanding of which populations are especially vulnerable to heat. Individuals 65 and over are among the most vulnerable to heat, (Fouillet et al. 2006; Lye 1997; Vaneckova et al. 2007) perhaps due to the increasing difficulty of thermoregulation with age as well as increased likelihood of impaired cardiovascular and renal function (Flynn 2005; Kenney 2001). The elderly may also be more likely to be taking medications, such as anticholinergics or antipsychotics, which inhibit the body's ability to recognize hyperthermia or initiate a thermoregulatory response (Martin-Latry et al. 2007). Besides physical and pharmacological risk factors, heat-related morbidity and mortality seem to have socioeconomic risk factors as well. Not having air conditioning has been identified as a major risk factor for health effects from heat (Naughton et al. 2002; O'Neill 2005), as has living alone (Fouillet et al. 2006; Naughton et al. 2002) and being of African American race (Kaiser et al. 2007; Medina-Ramon et al. 2006; O'Neill et al. 2003).

Although the association between heat and mortality is well studied, the association between heat and a measure of morbidity, such as hospital admissions, is less clear. In some studies, the rates of hospital admissions are lower than mortality rates during periods of high temperature, particularly among individuals with cardiovascular disease. Many of the cardiovascular deaths that occur due to heat and heat waves may occur too suddenly for the individual to receive medical attention (Linares and Díaz 2007; Mastrangelo et al. 2006). Similarly, in the United Kingdom, mortality has been found to rise during heat waves, but no significant increase in all-cause hospital admissions was detected. However, respiratory and renal admissions increased during heat waves (Kovats et al. 2004). In Adelaide, Australia, on the

other hand, mortality rates did not rise significantly while rates of hospital admissions have been found to increase during heat waves (Nitschke et al. 2007).

The effect of urban heat islands (UHIs) on the association of heat and mortality/morbidity is also not well studied. Certain urban neighborhoods can have higher temperatures than suburban or rural areas because a greater portion of urban areas are comprised of heat-absorbing impervious surfaces (e.g., asphalt or concrete) and less vegetation, which provides shade and lowers ambient temperature (Voogt and Oke 2003). For example, in a study of the variability of temperatures around Phoenix, AZ, higher temperatures were found in poorer neighborhoods where ethnic minorities reside, while wealthier neighborhoods, with lush landscaping, were cooler (Harlan et al. 2006). UHIs have been studied and modeled with respect to decreasing building cooling costs, decreasing air pollution and improving the aesthetic appeal of a neighborhood (Gartland 2008). However, in a literature review of the health effects of UHIs, only a small number of epidemiologic studies of the direct effects of UHIs on morbidity and mortality during heat events or heat waves have been conducted (Harlan et al. 2013, Uejio et al. 2011, Smargiassi et al. 2009, Smoyer 1998, Vandentorren et al. 2006).

Additionally, race may have been identified as a risk factor for death due to heat in past epidemiologic studies because individuals of non-white race may be more likely to live in areas with higher amounts of impervious surface. A large proportion of the difference in heat-related mortality between African Americans and Whites has been attributed to differences in air conditioning prevalence, but this does not explain all of the difference in effect by race (O'Neill 2005). In a study by Anderson and Bell (2009), the increase in heat mortality of a community was not statistically significant for an increase in the percent of the population that was African American when the following variables were controlled for: median household income, percent

unemployed, percent of the population without a high school degree, percent public transportation commuters, percent living in an urban setting, population size and percent with central air conditioning. This suggests that at least one of these variables accounts for racial disparities in heat vulnerability.

The effect of air pollution on the association between heat and morbidity/mortality is also not well studied. Ozone levels rise as a direct effect of temperature which speeds the reaction between nitrogen dioxide, solar radiation and volatile organic compounds to form ozone. This pollutant could therefore confound the effect of temperature on morbidity/mortality. Several studies have attempted to address the question of whether air pollutants confound and/or modify the relationship between temperature and mortality, but the results are conflicting (Basu and Samet 2002, Basu et al. 2008, Ebi and McGregor 2008, Ren et al. 2008).

The study of the direct effects of heat on morbidity and mortality presents several challenges. For one, very few hospital admission records or death certificates list “heat stroke” as a primary or contributing cause each year. Additionally, individuals dying at home due to heat stroke may not be discovered until their body temperature has dropped below levels required for a diagnosis of heat stroke (Klinenberg 2002). However, many studies have shown an increase in mortality with increasing temperature during the summer, suggesting that merely counting heat stroke cases does not fully capture the effects of heat on health (Basu and Samet 2002). As noted above, rates of mortality due to respiratory and cardiovascular diseases rise with temperature as well. Heat is similar to air pollution in that daily time series of exposures as well as daily time series of health effects (mortality or hospital admissions) are available in the United States. This allows the identification of trends in health effects during elevations in exposure, obviating the need for precise causes of death.

Another challenge is that humans do adapt to heat, both physiologically and culturally (e.g., through air conditioning use, siestas, cooler building design, etc.), making it unwise to use an absolute temperature threshold in heat wave health effects research. For example, temperatures which are considered normal in Phoenix, AZ in the summer are considered extremely high in Chicago, IL and are far deadlier in Chicago than in Phoenix. Cities most at risk to the health effects of heat have traditionally been cities in more temperate climates with lower air conditioning prevalence (Medina-Ramon and Schwartz 2007). Because a heat wave is generally considered a rare event, the National Weather Service definition is region-specific. However, the definition is not based on expectations of heat-health effects (2005; Robinson 2001). Other investigators have used definitions based on percentiles of temperature for a given city (Medina-Ramon et al. 2006; Schwartz 2005), but there is still heterogeneity among cities with this approach. Additionally, it is not clear that there is an "added heat wave effect", or an effect of long durations of high temperature, above and beyond the independent effects of single days of high temperature (Gasparrini and Armstrong 2011).

The health effects of temperature have been studied for many years, and municipalities and not-for-profits have begun to implement heat mitigation strategies (Rosenthal et al. 2008). Maps of vulnerability to heat (e.g., Reid et al. 2009 and Harlan et al. 2013) can be constructed to help cities identify which areas are most in need of targeted interventions during heat events, and heat health warning systems have been implemented in several cities (Bassil 2011) to inform the public and public services of impending heat events. Despite the actions being taken, it is important to understand the associations between heat and morbidity and which populations are

vulnerable to heat in order to improve vulnerability maps, heat health warning systems and to improve estimates of the present and future burden of heat in a changing climate.

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CHAPTER II

Vulnerability to Extreme Heat by Individual-Level and Neighborhood-Level Land Cover and Socioeconomic Characteristics Among the Elderly in Michigan, 1990-2007

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ABSTRACT

Background: With climate change and population aging, the health burden of high temperatures is a present and future concern, even in cooler climates. Adaptation strategies should target vulnerable populations. However, vulnerabilities due to land use and socio-demographic characteristics are not well understood.

Objectives: We examined how neighborhood-level green space and individual- and neighborhood-level socio-demographic characteristics modified the association between temperature and mortality among the elderly in 8 Michigan cities, during the period May-September, 1990-2007.

Methods: In a time-stratified case-crossover design, we regressed natural-cause mortality records against extreme heat, or an indicator for two-day average apparent temperature (AT) above the 95th or 97th percentile of warm season AT, on lag days 0-1 and 2-3. We examined effect modification by personal characteristics as well as characteristics of the decedent's ZIP code, including percent "non-green space" (computed from the National Land Cover Dataset) and characteristics of age, race, income, education and social isolation (from the U.S. Census) using interaction terms between each of the extreme heat indicator variables and characteristics. Results were pooled using random effects meta analysis.

Results: In models with multiple effect modifiers, non-married and male sex at the individual level as well as percent non-green space at the ZIP-code level modified the heat-cardiovascular mortality association. Black (individual level) and percent non-green space and percent over 75 years (ZIP-code level) modified the heat-respiratory mortality association.

Conclusions: Neighborhood green space and other demographic characteristics modify the association between heat and mortality among the elderly. Future vulnerability maps should incorporate the magnitudes of these modifiers.

BACKGROUND

In the U.S., the association between hot weather and mortality, especially cardiovascular and respiratory mortality, is well established (Anderson and Bell 2009; Braga et al. 2002; Curriero et al. 2002; Medina-Ramon and Schwartz 2007). With climate change and an aging population, heat-related mortality is of increasing concern. Public health measures to protect vulnerable populations from the effects of heat and heat waves are being adopted in many cities in the U.S. and around the world. Previously identified characteristics of vulnerability to heat-related morbidity and mortality include: advanced age, non-white race, poverty, lack of air conditioning or the financial resources to operate an air conditioner, social isolation, lack of green space (which provides shade and reduces ambient temperature) and low educational attainment (Reid et al. 2009; Sampson et al. 2013; Zanobetti et al. 2013). These characteristics have been used to construct vulnerability maps that can help communities determine where to focus resources during extreme heat (Harlan et al. 2013; Johnson et al. 2012; Reid et al. 2009).

However, in a validation study of one such vulnerability map, Reid and colleagues (Reid et al. 2012) showed that their map reflected vulnerability to mortality in general but not vulnerability to heat-associated mortality. Previously constructed vulnerability maps have been limited by using data that identify the characteristics of vulnerability or the health outcome of interest at a spatial resolution no finer than city- or county-level. Additionally, some of the area-level characteristics evaluated, such as percent of people living in poverty, percent of people with lower education, and percent green-space can be highly correlated with each other. For example, in the Detroit metropolitan area, census tracts with lower percent of vegetative cover are often the same census tracts where the population has the highest percent of people living in poverty and with the least education (White-Newsome et al. 2009). This situation makes evaluation of

the independent and relative contributions of these factors to heat vulnerability challenging. In epidemiologic terms, the relative influence of each of these potential effect modifiers, as well as the extent to which these effect modifiers confound each other, is poorly understood.

Cities in Michigan, a state with a temperate, four-season climate and relatively low air conditioning prevalence, have been shown to have high vulnerability to heat (Anderson and Bell 2009; Zanobetti and Schwartz 2008). We aim to determine the relative influence of individual- and ZIP code-level characteristics in modifying the short-term association between extreme heat and cardiovascular and respiratory mortality in Michigan using death records, land cover data, temperature data and socioeconomic data from 1990-2007.

METHODS

Data

The 10 counties in Michigan with populations greater than 200,000 were aggregated into 8 “cities” according to the county’s corresponding Metropolitan Statistical Area: Ann Arbor (Washtenaw County), Detroit (Wayne, Oakland and Macomb Counties), Flint (Genesee County), Grand Rapids (Kent County), Holland (Ottawa County), Kalamazoo (Kalamazoo County), Lansing (Ingham County) and Saginaw (Saginaw County) (Figure II.1). Within these cities, we used ZIP codes, US postal codes, as neighborhood units (Osypuk and Galea 2007).

Michigan death records from 1990-2007 were obtained from the Michigan Department of Community Health. These records included date of death, ZIP code of residence, marital status, race, age, sex and educational level. We restricted our data set to decedents 65 years and older and further classified the decedents as unmarried vs. married or separated, non-white vs. white, black vs. non-black, age 79 years or older vs. age 65-78 years, male vs. female and no high school degree vs. high school degree or higher. Primary causes of death were classified using the International Classification of Diseases codes from versions 9 and 10 (ICD-9 and ICD-10) as all-natural cause (ICD-9 < 800, 992 and E900.0; ICD-10 A-R, T67 and X30), heat-related (ICD-9 992 and E900.0; ICD-10 T67 and X30), cardiovascular (ICD-9 390-429; ICD-10 I0-I52), respiratory (ICD-9 460-466, 480-487, 490-492, 494-496; ICD-10 J9-J18, J40-J44, J47) and cardiorespiratory (cardiovascular or respiratory).

Daily mean temperature and dew point (means of at least 18 hourly observations) were obtained from the National Climatic Data Center (2012a) for the airport weather station nearest to each city with the most complete time series. These observations were used to calculate 2-day

running average of daily mean apparent temperature (AT, °C) for May-September, 1990-2007. AT incorporates both temperature and humidity and is calculated as:

$$AT = -2.653 + (0.994 \times \text{ambient temperature}) + (0.0153 \times (\text{dew point temperature})^2)$$

(O'Neill et al. 2005)

We obtained neighborhood-level socio-demographic characteristics from 2 sources: Decennial Census Long Form data in 2000 ZIP Code Tabulation Areas (ZCTAs, polygons constructed by the U.S. Census Bureau approximating ZIP codes, which are not true polygons), for 1990 and 2000 (2006) and 5-year average (2006-2010) estimates in 2010 ZCTA boundaries from the American Community Survey (2012b). We extracted the following characteristics for each study ZCTA: percent 65 years or older and living alone, percent non-white, percent black, percent aged 75 years and older, percent without a high school degree, percent of households at or below the poverty level and household median income. We also obtained ZCTA population-weighted centroids for 2000 and 2010 ZCTAs (2012c).

Land cover classifications at a resolution of 30 x 30 m were obtained from the Multi-Resolution Land Characteristics Consortium for 1992, 2001 and 2006 (U.S. Department of the Interior 2012). We further classified these data as “green space” vs. “non-green space” (Figure II.1) and calculated the percent area non-green space in each ZCTA using ZCTA 2000 and 2010 Census TIGER/Line shapefiles (2012d).

We estimated annual values for land cover and socio-demographic characteristics for each ZCTA by linearly interpolating the decadal values. For example, 1993 land cover values were obtained by taking a weighted average of the 1992 and 2001 values. For years outside the data interval we used the annual value of the closest year in the data interval (e.g., land cover values for years 1990-1991 were estimated using the 1992 land cover value).

Analysis

We employed a time-stratified case-crossover design, with controls selected on the same days of the week in the same month as the cases (except the case day) (Janes et al. 2005). Confounding by individual-level characteristics and characteristics that vary over longer than 1 month are automatically controlled for by design. First, we performed the time-stratified case-crossover analysis using Poisson regression (with indicator variables for each combination of year, month and day-of-week) to examine the association between deaths and 4, 2-day means of AT (lag days 0-1, 2-3, 4-5 and 6-7), all used simultaneously and modeled using natural cubic splines with 6 degrees of freedom. Lags of 2-day mean AT, instead of single day AT, were used to reduce collinearity between the temperature exposures. The results of these models were used to make decisions about the thresholds for extreme heat as well as the number of lags of 2-day mean AT to include in subsequent models. Then, we performed the case-crossover analysis using conditional logistic regression which allowed us to assess effect modification (vulnerability) by including interaction terms between the time-varying exposure (AT) and the individual- or ZCTA-level characteristic, a feature of this design that has not often been taken advantage of (Carracedo-Martinez et al. 2010).

We performed our vulnerability analysis in the following order:

1. We ran the following model for each city for each cause of death (cardiovascular or respiratory), using 2 extreme heat thresholds (95^{th} or 97^{th} percentile of 2-day mean AT) and each effect modifier (e.g., percent non-green space):

$$\text{logit(mortality)} = \beta_1 EH01 + \beta_2 EH23 + \beta_3(EH01 \times EM) + \beta_4(EH23 \times EM)$$

where EH01 is an indicator variable for the mean of AT on lag days 0-1 being above the extreme heat threshold in that city, EH23 is an indicator variable for the mean of AT on lag days 2-3

being above the extreme heat threshold, and EM is the effect modifier. Individual-level effect modifiers (e.g., non-married) were introduced in the model as indicator variables.

2. Using the estimates of $\exp(\beta_3)$ (odds ratio (OR) of mortality for a unit increase in the effect modifier during extreme heat) and $\exp(\beta_3 + \beta_4)$ (sum of the 2 individual 2-day ORs) obtained for each of the 8 cities, we performed an inverse-variance weighted random effects meta analysis for each cause of death, extreme heat threshold and effect modifier. For the continuous effect modifiers, results were calculated for the interquartile range (IQR) increase which we calculated among the cases across all 8 cities (Table II.1).

3. In the final model for each city, we first included modifiers from each vulnerability category of age, race, sex, income, education, social isolation and green space. Then, from each of these categories at the level at which they were available (individual- or ZIP code-level, we selected the modifier with the strongest association in step 2 and combined these individual- and ZCTA-level modifiers into a single model. The final model had 11 effect modifiers and was given by:

$$\text{logit(mortality)} = \beta_1 EH01 + \beta_2 EH23 + \beta_3(EH01 \times EM_1) + \beta_4(EH23 \times EM_1) + \beta_5(EH01 \times EM_2) + \beta_6(EH23 \times EM_2) + \ldots + \beta_{23}(EH01 \times EM_{11}) + \beta_{24}(EH23 \times EM_{11})$$

To assess whether there was still residual spatial correlation, we derived the conditional logistic regression residuals[23] for each matched set with identical characteristics using the SAS macro mcstrat[24]. We then constructed the empirical semi-variograms of the residuals using the centroid of each matched set's ZCTA to calculate distances and we evaluated them for indication of residual spatial dependence in the data.

4. We then conducted meta analyses as in step 2, although we now used a multivariate random effects meta analysis which accounts for the covariance between the betas. We also

calculated best linear unbiased predictions for individual cities (a shrunken average of the city-specific result and the meta analysis result) for each of the effect modifiers.

We performed data management and analyses in ArcGIS 10, SAS 9.2 and R 2.15. In ArcGIS we used the “near” and “tabulate data” tools. Our analyses used the glm, coxph, fields, gstats and mvmeta packages in R.

RESULTS

With the exception of Holland, the eight cities considered in this study were similar to one another for temperature and individual characteristics. In Holland, the percent of decedents who were non-white was too small to allow for analyses of this potential modifier, so race variables were excluded from the full models. Additionally, the percent of deaths coded as heat-related was too small in any city to use this cause of death as an outcome.

ZCTA characteristics ranged more widely than temperature and individual characteristics between cities. Ann Arbor ZCTAs had little non-green space (the 75th percentile of percent non-green space was 29.7%) while Detroit ZCTAs had a high percentage of non-green space (the 25th percentile was 68.9%). Among the ZCTA characteristics, percent below the poverty level, median income, percent non-white, percent black and percent without a high school degree were moderately to highly correlated with each other (Table II.2). We did not have information on Hispanic ethnicity at the individual level, and percent non-white and percent black were highly correlated, so in subsequent analyses, the only category of race/ethnicity which we focused on was black race.

In analyses of the association between extreme heat and mortality without accounting for effect modification, effects were strongest for AT01 and AT23 above the 95th percentile (e.g., in Detroit, Figure II.2). In light of this result, in our effect modification analyses we only considered these two 2-day lags above the 95th percentile threshold.

Among the vulnerability characteristics, when each was examined in a separate model, the individual-level characteristics non-married and black race and the ZCTA characteristics percent non-green space, percent black and percent below poverty level modified the association between extreme heat and cardiovascular mortality when extreme heat was defined as 2-day AT

average above the 95th and/or the 97th percentile. Being unmarried was protective against extreme heat-associated cardiovascular mortality, with an OR less than 1 (Figure II.3A). The ZCTA percent aged 75 years and older modified the association between respiratory mortality and extreme heat (Figure II.3B). Percent below poverty level and median income in a ZCTA had similar effects, so we only included percent below poverty level in subsequent models.

For models containing all 11 modifiers, being non-married and male (individual-level characteristics) modified the extreme heat-cardiovascular mortality association, controlling for the other characteristics. Modifiers of the extreme heat-respiratory mortality association differed from those of the extreme heat-cardiovascular mortality association. Respiratory modifiers included black race (at the individual level) and the percent of individuals 75 years and older (at the ZCTA level).

In Q tests of heterogeneity, we found significant heterogeneity in the coefficient estimates for 3 extreme heat-cardiovascular mortality modifiers for cardiovascular mortality: percent non-green space, percent black and percent with no high school degree, and the best linear unbiased predictions for these effect modifiers are presented in Figure II.4 A-C. We also found significant heterogeneity for 2 extreme heat-respiratory mortality modifiers: no high school degree (individual level) and percent with no high school degree (ZCTA level) (Figure II.5 A-B). Some of these city-specific modifying effect estimates were significantly greater than 1, e.g., percent non-green space in Grand Rapids, Lansing and Saginaw.

DISCUSSION

Some of the potential effect modifiers were moderately correlated, reinforcing the need to account for confounding among characteristics of vulnerability when assessing vulnerability to heat. Even after accounting for social isolation, race, education, age and sex to the extent that this information was available at the individual and neighborhood level, the effect of percent non-green space persisted, with, for example, a 1.44 (95% CI = 1.04, 2.00) higher risk of cardiovascular mortality during extreme heat for in IQR increase (51.6%) in percent non-green space in Grand Rapids.

The association between non-green space and heat-associated mortality is somewhat consistent with other epidemiologic studies looking at the association between heat health effects and land cover or satellite-derived land surface temperature and sociodemographic characteristics at a fine geographic resolution. In Montreal, satellite-derived land surface temperature in a postal code modified the association between warm season temperature and daily mortality among individuals in postal codes with higher property values, but land surface temperature did not modify this association in postal codes with lower property values, where the temperature-mortality association was higher in general. This suggested an influence of the urban heat island effect on heat-associated mortality, though only in the absence of substantial socioeconomic deprivation (Smargiassi et al. 2009). In a study of the 2005 summer in Phoenix, both percent impervious surface and land surface temperature in a census block group were associated with heat distress calls, controlling for a variety of other socioeconomic factors (Uejio et al. 2011). However, in a similar study of the 1999 summer in Philadelphia, none of the built environment measurements—vegetation, land surface temperature or percent impervious surface—were associated with heat deaths in a census block group (Uejio et al. 2011). In a

separate study of Phoenix heat deaths in census block groups from 2000-2008, models incorporating either vegetation or land surface temperature in conjunction with socioeconomic factors best fit the data (Harlan et al. 2013). Our study, which used a design that allowed us to control for both individual-level demographic factors and area-level factors, still showed a deleterious effect of lack of vegetation; these findings suggest a role for urban-heat-island mitigation strategies, such as tree plantings.

Despite the finding in 3 of the above studies and our own study that lack of surface vegetation contributes to vulnerability to heat-associated morbidity and mortality, the relative importance of this effect and of socioeconomic characteristics may be highly dependent on the city or region being studied as discussed above. Even within Michigan, we found heterogeneity in effect estimates for green space, race and education at the neighborhood level and education at the individual level between cities.

Few studies have explicitly evaluated the role of green space in human health. In addition to the studies of vegetation and heat-associated morbidity and mortality mentioned above, self-reported health and well-being indicators have been positively associated with green space (de Vries et al. 2003; Maas et al. 2006; Takano et al. 2002; Tanaka et al. 1996). A study in England found a significant difference in the association between income inequality and mortality across groups with differing exposure to green space. Incidence rate ratios for all-cause mortality and circulatory diseases were higher for residents living in less green areas than in areas with more green space (Mitchell and Popham 2008). Green areas may protect health by reducing air pollution, the urban heat island effect and promote physical activity for a healthier lifestyle.

Our study was limited by the still relatively coarse spatial resolution (ZIP code) of the case location of residence. For example, the relative importance of, for example, having a tree

above one's house vs. a lush park down the street cannot be disentangled at the ZIP code level. Future research will use more finely resolved residence locations. Also, the number of decedents of other races was too small in Michigan to allow for testing effect modification by other races, and the lack of availability of individual-level socioeconomic indicators besides age and marital and educational status prohibited us from understanding how individual-level cultural or economic characteristics may confound the observed effect modification by race.

Our finding that being unmarried was protective against extreme-heat-related cardiovascular mortality was surprising given previous research. This variable may be serving as a proxy for living in multigenerational single family homes or elderly housing in which the elderly individual may have received a higher level of care and protection against the effects of extreme heat.

We did not have individual-level or ZIP code-level information about air conditioning prevalence. However, previous research has found that having the financial resources to operate an air conditioner are important in addition to owning an air conditioner (Klinenberg 2002; Sampson et al. 2013; Sheridan 2007). We believe that percent below the poverty level may be a proxy for air conditioning usage at the ZIP code level.

In summary, lack of green space modified the association between extreme heat and cardiovascular mortality in 3 Michigan cities, even after controlling for both individual-level and neighborhood level socioeconomic characteristics. The influence of green space, race and education varied between cities and by mortality outcome. Future research will use more finely resolved spatial information and will develop methods to quantify and display maps of vulnerability to heat in Michigan.

TABLES

Table II.1. Individual and Zip Code Tabulation Area (ZCTA)-level characteristics of cases (decedents) aged 65 years and older in Michigan study cities, 1990-2007.

	Ann Arbor	Detroit	Flint	Grand Rapids	Holland	Kalamazoo	Lansing	Saginaw
Mean daily number of deaths, May-September								
All-natural-cause	3.0	62.0	6.5	7.2	2.6	3.3	3.3	3.7
Cardiovascular	1.0	24.2	2.5	2.5	0.9	1.1	1.2	1.3
Heat-related	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
Respiratory	0.2	4.6	0.5	0.7	0.2	0.3	0.3	0.3
Percentiles of 2-day mean daily mean apparent temperature (°C), May-September								
95th	28.9	29.5	28.1	28.5	28.5	28.7	28.2	27.9
97th	29.9	30.5	29.1	29.5	29.5	29.7	29.2	29.0
Percent of cases with the following characteristics								
Non-married	36.5	36.3	38.4	38.5	43.1	38.1	36.5	39.4
No high school degree	28.5	38.6	40.3	37.2	43.8	33.1	31.4	44.8
Male	42.7	44.6	44.4	43.5	44.4	42.7	42.0	45.0
Non-white	10.6	21.5	14.3	5.7	0.9	5.7	7.0	12.0
Black	9.7	20.9	13.8	5.3	0.3	5.2	6.2	11.7
Aged 79+ years	62.3	56.1	54.1	62.5	65.4	61.9	61.2	58.9
Number of ZCTAs and 25th-75th percentiles of ZCTA characteristics among the cases[1]								
Number of ZCTAs	26	177	33	39	22	23	23	28
Percent non-green space	8.6-29.7	68.9-94.7	12.1-53.8	43.8-73.9	17.5-24.7	8.7-48.4	25.0-53.3	9.7-46.4
Percent non-white	7.5-31.8	5.2-60.8	4.7-30.1	6.0-22.0	2.8-10.2	8.1-20.9	7.2-25.7	3.4-23.7
Percent black	3.0-22.8	1.4-49.6	1.7-24.5	1.6-12.2	0.2-1.4	3.7-13.9	2.1-13.5	0.6-15.2
Percent aged 65+ years and living alone	5.0-7.7	8.0-12.7	7.6-11.4	7.2-11.0	6.1-9.9	7.6-10.0	6.8-9.1	9.3-13.0
Percent below poverty level	4.5-14.3	4.3-19.2	6.1-22.6	6.2-12.3	3.7-7.4	6.3-20.6	7.6-20.3	7.7-18.8
Median income	42.4-62.1	32.4-55.0	30.4-48.6	35.5-50.4	43.4-53.5	31.7-46.6	33.0-47.2	26.8-45.5

(thousands of dollars)								
Percent without high school degree	4.8-13.0	12.0-27.5	11.9-23.2	11.1-21.4	10.9-17.9	8.1-16.6	7.5-17.0	13.5-24.3
Percent aged 75+ years among those aged 65+	42.1-47.0	40.9-50.2	39.3-45.6	43.2-52.8	44.7-51.6	43.5-50.8	41.4-50.5	40.9-53.7

[1] Among all the cities combined, the IQR increases in percent non-green space, percent non-white, percent black, percent 65 years and older and living alone, percent below the poverty level, median income, percent black, percent without a high school degree and percent 75 years and older were 51.6%, 29.1%, 22.7%, 4.5%, 13.1%, $20,200, 13.5% and 9.1%, respectively.

Table II.2. Case-weighted correlations among ZIP Code Tabulation Area characteristics, 1990-2007.

	% Non-Green	% Non-White	% Aged 65+ and Alone	% Below Poverty	Median Income	% Black	% No High School	% Aged 75+
% Non-Green	1	0.46	0.45	0.4	-0.38	0.45	0.51	0.18
% Non-White		1	0.09	0.81	-0.58	0.99	0.6	-0.03
% Aged 65+ and Alone			1	0.16	-0.28	0.1	0.25	0.49
% Below Poverty				1	-0.76	0.78	0.77	0
Median Income					1	-0.58	-0.81	0.04
% Black						1	0.59	-0.06
% No High School							1	-0.18
% Aged 75+								1

FIGURES

Figure II.1. Land cover in Michigan's Lower Peninsula in 2001 (U.S. Department of the Interior 2012).

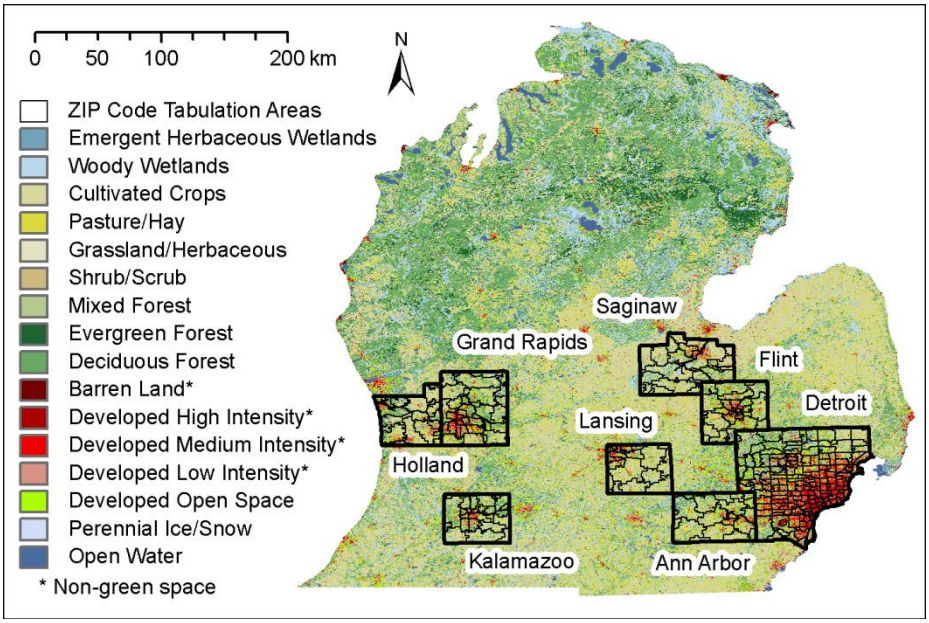


Figure II.2. Partial regression plots of associations between mortality among individuals 65 years and older and 4, 2-day lags of 2-day mean daily mean apparent temperature (AT) as natural cubic splines with 6 degrees of freedom (modeled simultaneously), Detroit, Michigan, 1990-2007.

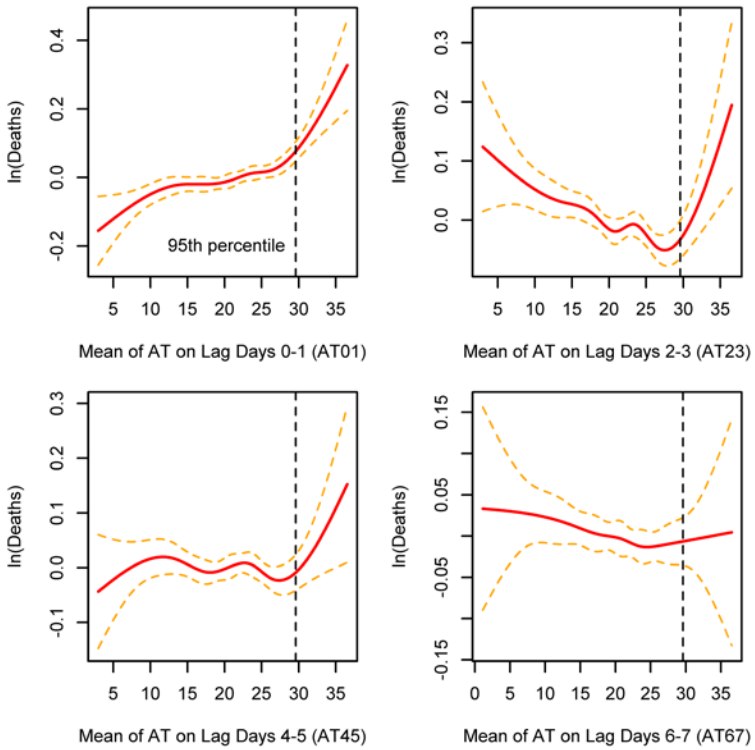


Figure II.3. Pooled (among the 8 study cities) odds ratios (ORs) and 95% confidence intervals for the modification of the association between cardiovascular or respiratory mortality and extreme heat (2-day running average of daily mean apparent temperature (AT) above the 95th or 97th percentile on lag days 0-1 and 2-3) for the presence of an individual-level or an interquartile range increase in a ZIP code-level effect modifier, Michigan, 1990-2007.

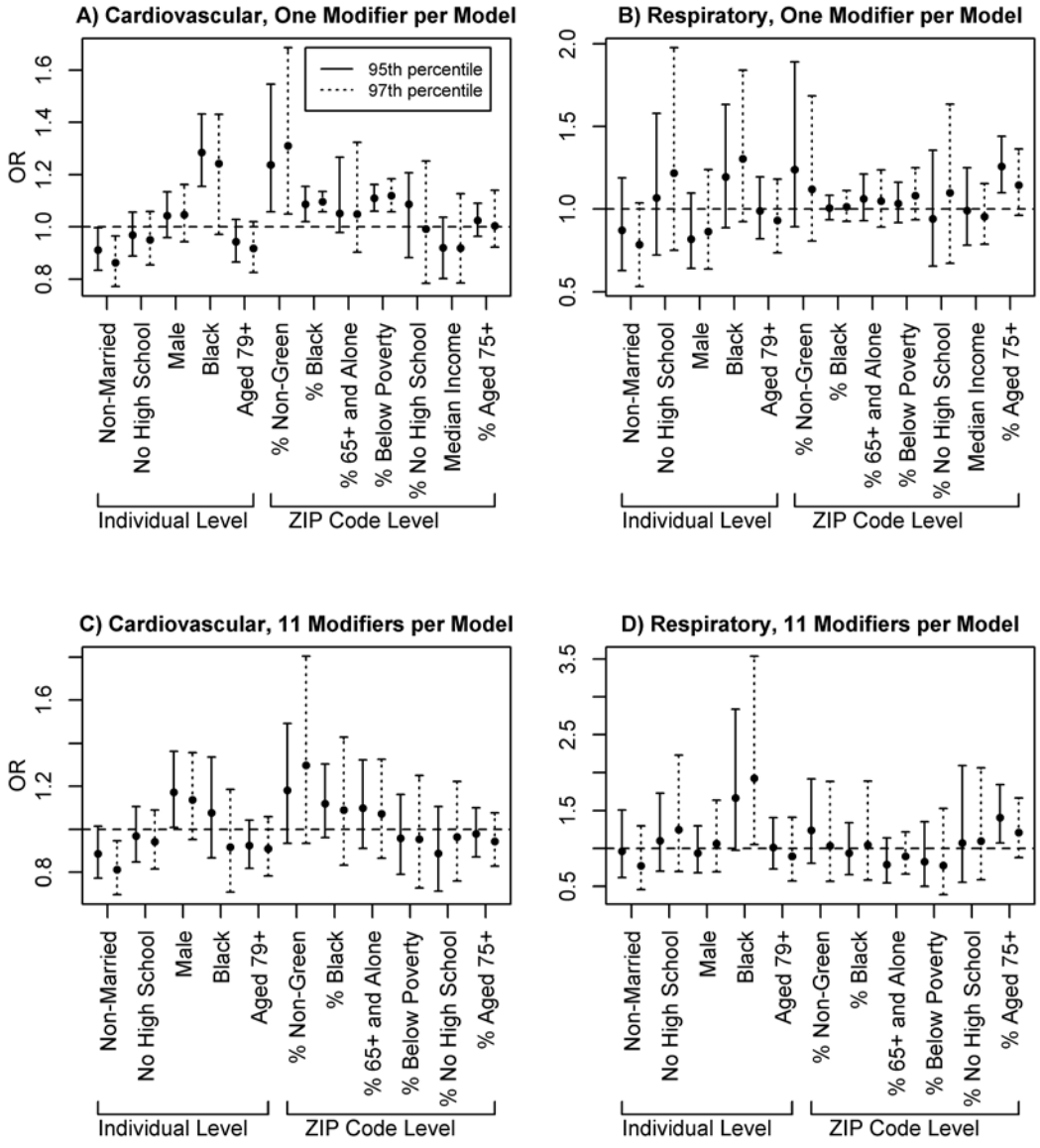


Figure II.4. Odds ratios (ORs) and 95% confidence intervals for the modification of the association between mortality among decedents 65 years and older and extreme heat (2-day mean apparent temperature above the 95th or 97th percentile on lag days 0-1 and 2-3) for cardiovascular mortality for an interquartile range increase in the percentages in a ZIP code of A) non-green space , B) residents of black race and C) residents without a high school degree, Michigan, 1990-2007.

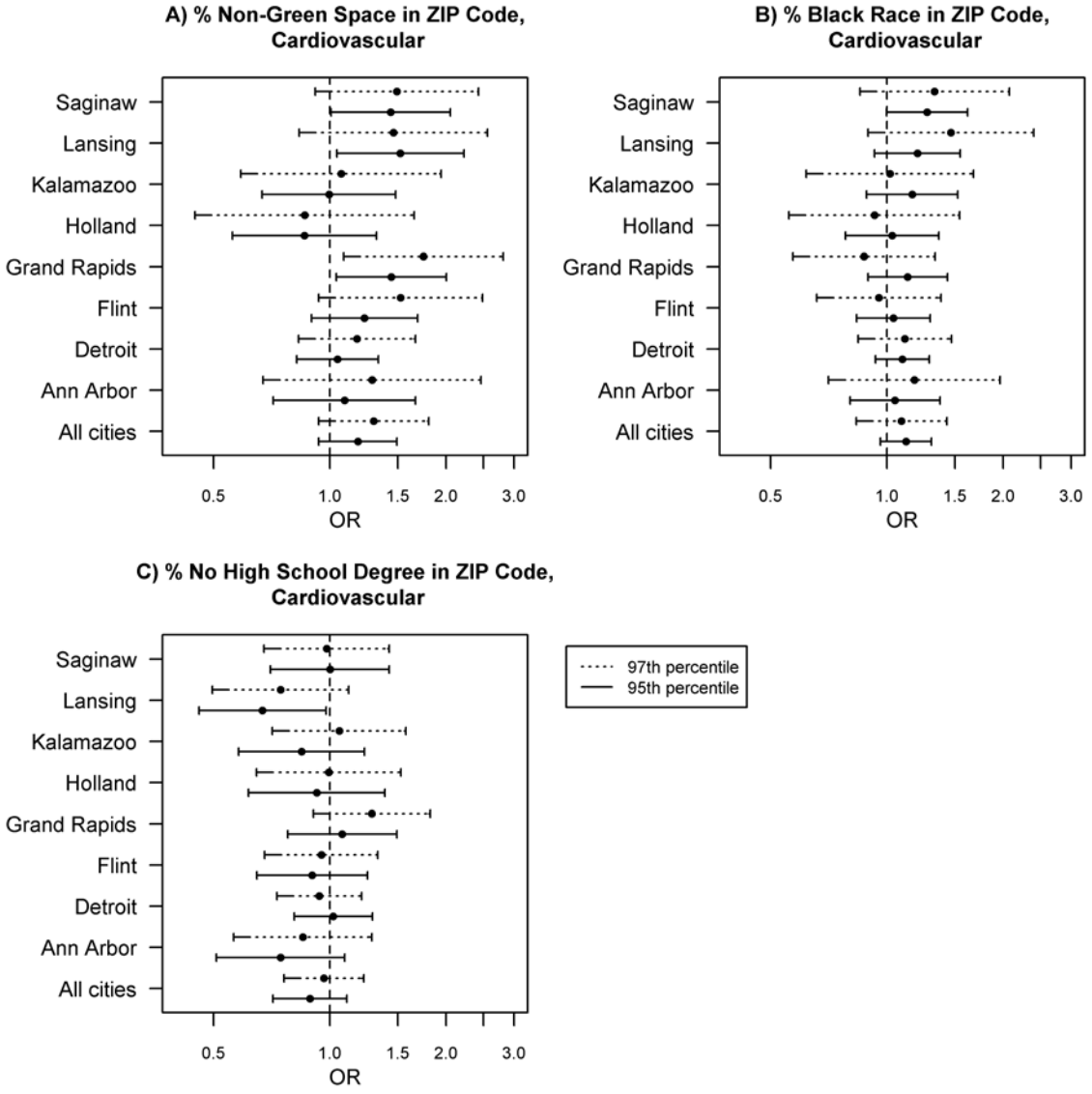
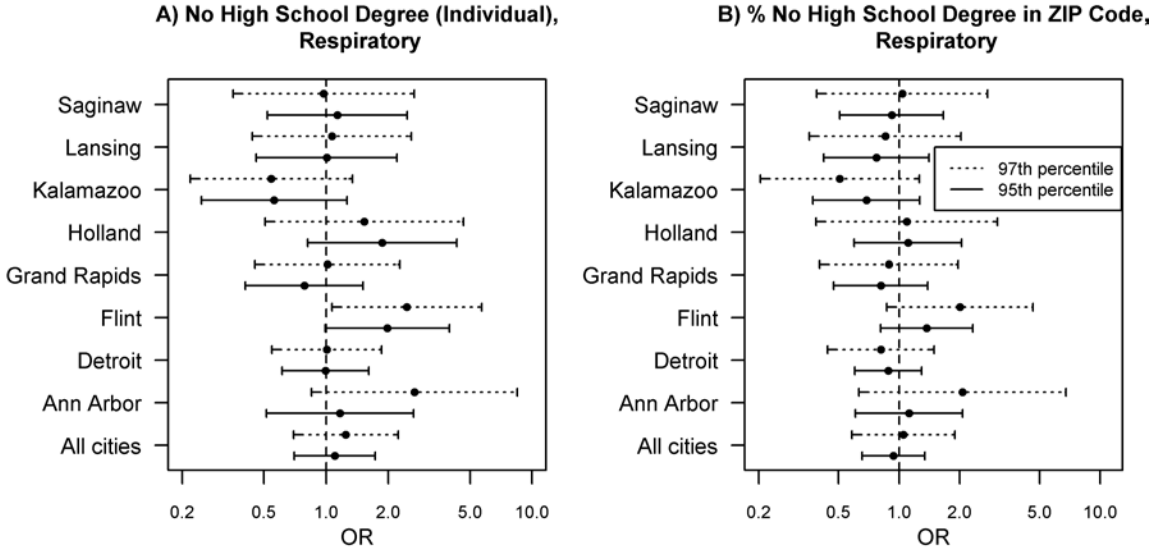


Figure II.5. Odds ratios (ORs) and 95% confidence intervals for the modification of the association between mortality among decedents 65 years and older and extreme heat (2-day mean apparent temperature above the 95th or 97th percentile on lag days 0-1 and 2-3) for respiratory mortality for A) no high school degree and B) an interquartile range increase in the percent of residents without a high school degree in a ZIP code, Michigan, 1990-2007.



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CHAPTER III

Heat, Heat Waves and Hospital Admissions Among the Elderly in the United States, 1992-2006

Submitted to Environmental Health Perspectives

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Abbreviations:
AT: daily mean apparent temperature
AT01: the mean of AT over lag days 0 and 1 (the day of and the day before hospital admission)
$AT01_{MH}$: moderate heat, or continuous AT01 in °C below a city-specific percentile threshold, e.g., the 95th percentile of warm-season (May-September) AT01
$AT01_{EH}$: extreme heat, or an indicator variable taking the value of 1 if AT01 on that day is above a city-specific percentile threshold, e.g., the 95th percentile of warm-season (May-September) AT01, and zero otherwise
CDD: cooling-degree day (annual sum of daily mean temperatures below 18.3 °C)
CI: confidence interval
COOP: National Climatic Data Center's Cooperative Summary of the Day
CVD: cardiovascular
DTR: diurnal temperature range

HDD: heating-degree day (annual sum of daily mean temperatures above 18.3 °C)
Heat wave: several consecutive days of extreme heat
ICD-9-CM: The International Classification of Diseases, Ninth Revision, Clinical Modification
IQR: Interquartile range
MA: daily maximum temperature
MI: daily minimum temperature
MT: daily mean temperature
OR: odds ratio
Resp: respiratory

ABSTRACT

Background: Heat-wave frequency, intensity and duration are increasing with global climate change. The association between heat and mortality in the elderly is well documented, but less is known regarding the associations with rates of hospital admissions.

Objectives: To determine associations between moderate and extreme heat, heat waves and hospital admissions for non-accidental causes among Medicare beneficiaries aged ≥65 years in 114 cities across 5 U.S. climate regions.

Methods: We used Medicare inpatient billing records and city-specific temperature, humidity and ozone data from 1992-2006 in a time-stratified case-crossover design to estimate the association between hospitalization rates and moderate and extreme heat and heat waves (apparent temperature above the 95th percentile over 2-8 days). In sensitivity analyses we additionally considered confounding by ozone and holidays, different temperature metrics, alternative thresholds of extreme heat and more complex models of the exposure-response relationship.

Results: Extreme heat over the past 2 days was associated with an 8% (95% CI: 7%, 9%) higher rate of all-cause hospital admissions. In cause-specific analyses, extreme heat was associated with higher rates of hospitalizations for cardiovascular, renal and respiratory diseases, with admission rates increasing by 43% (95% CI: 37%, 50%) for renal diseases. Associations between extreme heat and hospitalizations for renal diseases persisted up to 8 days. The sum of heat effects over longer lags was protective for admissions for cardiovascular and respiratory diseases.

Conclusion: Extreme heat is associated with increased rates of hospital admission among the elderly in the U.S., and those with renal disease are particularly susceptible.

BACKGROUND

Heat waves, or extreme heat events, are predicted to increase in frequency, intensity and duration with climate change (IPCC 2007). The elderly are more vulnerable to heat-related mortality, so the changing population structure (Vincent and Velkoff 2010) may also lead to an increased health burden from heat. The associations between temperature and mortality are well studied (Gosling et al. 2009; Hajat and Kosatsky 2010). In the U.S., associations between heat and daily mortality are stronger in cities with milder summers and lower air conditioning prevalence (Anderson and Bell 2009; Anderson and Bell 2011; Curriero et al. 2002; Medina-Ramon and Schwartz 2007; O'Neill and Ebi 2009). Although extreme heat events in the U.S. are associated with increased deaths (Ostro et al. 2009; Semenza 1996), the role of heat-wave duration vs. intensity as a health determinant remains unclear (Anderson and Bell 2011; Gasparrini and Armstrong 2011).

Studies examining associations between heat and hospital admissions have had mixed results (Ye et al. 2012, Turner et al. 2012). For example, in London, England, a 1995 heat wave was not associated with total hospital admissions but was associated with hospitalizations for respiratory and renal diseases and increased mortality (Kovats et al. 2004). On the other hand, heat waves in Adelaide, Australia have been associated with increased hospitalizations but not increased mortality (Nitschke et al. 2007). In 12 European cities, respiratory admissions increased with temperature in Mediterranean and North-Continental cities, but associations between temperature and cardiovascular admissions tended to be negative and non-significant (Michelozzi 2009).

Understanding associations between heat waves and hospital admissions in the U.S. is important to predict how climate change may increase the future burden of heat-related

morbidity; to identify vulnerable subpopulations for potential interventions; and to refine activation thresholds for heat health warning systems.

We analyzed Medicare inpatient billing records from 114 cities in the U.S. from 1992-2006 to evaluate 1) the associations between moderate and extreme heat measured as daily mean apparent temperature (AT) and all-cause and cause-specific hospital admissions among elderly Medicare beneficiaries residing in 5 U.S. climate regions, 2) the added effect of extreme heat durations of 4-8 days, 3) whether observed associations are confounded by ambient ozone levels and holidays and 4) the sensitivity of our findings to the choice of temperature metric, heat thresholds and the modeling of the exposure-response relationship.

METHODS

Study cities and regions

The 200 counties with the highest number of cardiovascular hospital admissions in 2004-2006 were assigned to their respective Metropolitan Statistical Areas to form the study cities, which were then assigned to the U.S. Department of Energy, Energy Information Administration's 5 climate regions as previously described (Zanobetti et al. 2012 and Appendix A).

Health outcomes

We obtained emergency hospital admissions for individuals 65 years and older from 1992-2006 from the U.S. Centers for Medicare and Medicaid Services MedPAR billing records. Ninety-seven percent of Americans aged 65 and older receive Medicare insurance coverage. We categorized admissions according to the primary admission ICD-9-CM codes as all-cause (all ICD-9-CM codes < 800), cardiovascular (CVD, 390-429), heat (992 and E900.0), renal (580-589) and respiratory (resp, 480-487, 490-492 and 494-496). The “heat” category also included secondary causes of admission related to heat. The research was approved by the Institutional Review Boards at Harvard University and University of Michigan.

Environmental variables

We obtained daily temperature and dew point data for each city from the National Climatic Data Center Cooperative Summary of the Day station files (National Climatic Data Center 2010b). Data from a single monitor for each city were used except in 6 cities where multiple observations were missing from all the nearby monitors, in which case hourly data from the National Climatic Data Center’s Integrated Surface Database Lite (National Climatic Data

Center 2010a) were converted to daily values. For 25 stations missing dew point data, dew point data were obtained from the nearest station with dew point data. We calculated AT using daily mean temperature (MT) and dew point (AT(°C) = -2.653 + (0.994 · MT) + (0.0153 · (dew point^2)) (Kalkstein 1986). We excluded 20 cities from our analysis which were missing AT measurements on at least 15% of the study days.

We chose AT as our main heat exposure metric to jointly account for effects of temperature and humidity, but we also addressed the sensitivity of our results to the alternative metric choices of MT, daily minimum temperature (MI), daily maximum temperature (MA) and diurnal temperature range (DTR, the difference between MA and MI).

Because ambient ozone levels rise during hot weather and have been linked with increased rates of hospital admissions, ozone can potentially confound associations between heat and hospital admissions (Medina-Ramón et al. 2006). We obtained ozone data from the U.S. Environmental Protection Agency's Air Quality System, and daily 8-hour averages were calculated and standardized as described previously (Medina-Ramón et al. 2006). For ozone analyses, we excluded an additional 10 cities from our analysis which were missing ozone measurements on at least 15% of the study days.

Main Statistical Analysis

We used a time-stratified case-crossover design as previously described (Medina-Ramon and Schwartz 2007) to evaluate the association between heat and hospital admissions in each city using data on hospital admissions occurring between May and September. Control days were chosen such that cases and controls were matched on calendar month and day of week. We applied conditional logistic regression using the coxph package in R, and specified robust

variance estimators with clustering on the unique combinations of year, month and day-of-the-week.

To reduce collinearity between temperature lags in our models, for each metric, we modeled temperature exposure as 2-day means of lags instead of individual lags. Specifically, we used the following lag metrics: AT01 (mean of ATs on the day of and day prior to the hospital admission) and AT23, AT45, and AT67 (means of ATs 2 and 3, 4 and 5, and 6 and 7 days before hospital admission, respectively). This is a constrained distributed lag model where lags 0 and 1 are constrained to have the same effect, lags 2 and 3 are constrained to have the same effect, and so on (Armstrong 2006; Schwartz et al. 2004).

We modeled moderate heat as a linear term of 2-day mean AT, taking a value in °C unless 2-day mean AT was above the city-specific 95th percentile of warm-season (May-September) 2-day mean AT, in which case it took a value of 0. We also included an indicator variable for extreme heat, taking a value of 1 if AT was above the city-specific 95th percentile of warm-season 2-day mean AT, and 0 otherwise. To distinguish between effects of heat intensity and duration, we included a term for extreme heat duration in additional models, and we modeled this extreme heat duration term as an interaction of extreme heat—the product of each of 2, 3 or 4 extreme heat indicator variables for heat waves of at least 4, 6 or 8 days in duration. For example, the model of the effect of being in a heat wave for at least 8 days, in addition to the parameters for each matched set of cases and controls which were conditioned out of the likelihood function, included the 4 linear terms for moderate heat at each 2-day lag ($AT01_{MH}$, $AT23_{MH}$, $AT45_{MH}$ and $AT67_{MH}$), the 4 indicator variables for extreme heat ($AT01_{EH}$, $AT23_{EH}$, $AT45_{EH}$ and $AT67_{EH}$) and the extreme heat duration term, or the product of the 4 extreme heat indicator variables:

$$\text{logit(hospital admission)} = \beta_1 AT01_{MH} + \beta_2 AT01_{EH} + \beta_3 AT23_{MH} + \beta_4 AT23_{EH} + \beta_5 AT45_{MH} + \beta_6 AT45_{EH} + \beta_7 AT67_{MH} + \beta_8 AT67_{EH} + \beta_9 (AT01_{EH} \cdot AT23_{EH} \cdot AT45_{EH} \cdot AT67_{EH}) \quad [1]$$

Because the models were comprised of linear terms and indicator variables, meta analysis using the city-specific results was straightforward. To understand the cumulative effects of moderate and extreme heat over longer time periods, in additional models we added terms for moderate and extreme heat on lag days 8-9, 10-11, 12-13, 14-16 and 17-20 and then summed the coefficients from lag days 0-20.

We calculated odds ratios (ORs) and 95% confidence intervals (CIs) from this model for 1) a 1 °C increase above a heat threshold, 2) an interquartile range (IQR) increase in temperature and 3) extreme temperature above a threshold (e.g., 95^{th} percentile).

Finally, we pooled city-specific results in each of the 5 climate regions and overall in a random effects meta analysis using inverse variance weighting (DerSimonian and Laird 1986) using the meta package in R, and Q statistics for heterogeneity within and between climate zones were calculated. All analyses were performed in R 2.15 (R Development Core Team 2011).

Sensitivity Analyses

We evaluated confounding by ozone on lag days 0-1 and the holidays Memorial Day, Independence Day and Labor Day (which all occur in the first or last week of the month) by comparing the ORs for AT from models with and without inclusion of the confounders (ozone or holidays).

We examined the sensitivity of our results to percentile threshold of extreme heat by modeling extreme heat as indicator variables for AT above the 90^{th} percentile. We also modeled different metrics for temperature (MT, MI, MA or DTR) in place of AT.

In a time-stratified case crossover design, each case's controls are selected from the same time stratum as the case, and seasonal effects and long-term time trends are assumed to vary inconsequentially within each time stratum. In our main models, this time stratum was a month, for a total of 5 time strata per year, each 30 or 31 days long. To examine the sensitivity of our results to the length of the time stratum, we used either 6 time strata (each 25 or 26 days long) or 4 time strata (each 38 or 39 days long) per year in separate models.

We examined the sensitivity of our results to the inclusion of all the months in which heat waves occurred (April-October) which required the addition of a term for cold temperatures (see Appendix A). We also attempted to identify heat and cold thresholds using the SiZer method, which identifies significant increases or decreases in locally weighted polynomial smoothers for different spans of the smoother (see Appendix A).

RESULTS

We examined the association between heat and rates of hospitalization in 114 cities broadly distributed across the U.S. (Appendix A, Figure A.1).

Cardiovascular, respiratory and renal admissions accounted for approximately 24%, 8% and 1% of all-cause admissions in each climate zone from May through September (Table III.1). Heat-related admissions were uncommon, accounting for only 0.1% of all-cause admissions. In hotter climates, the IQR for AT was smaller than in cooler climates, though the number of days meeting the definitions for 4-, 6-, and 8-day long heat waves were similar between climates.

By modeling AT as consecutive 2-day means of AT, the model terms were only weakly to moderately correlated, as hoped (Pearson correlation coefficients between 2-day means of AT within each climate zone ranged from 0.10 to 0.43, with the maximum coefficient in climate zone 1).

Pooled associations (across all cities) between hospital admissions and moderate heat as well as extreme heat varied by cause of admission and lag (Figure III.1). Among the individual 2-day lag periods, lag 0-1 showed the strongest association, and effects were much stronger for extreme heat than for moderate heat for each cause of admission (Figure III.1, see Appendix A, Figure A.3 for IQR increases in moderate heat). Among the causes of admission, moderate and extreme heat were most strongly associated with admissions for renal disease (for a 1 °C increase in $AT01_{MH}$, OR = 1.01; 95% CI: 1.01, 1.01 and for $AT01_{EH}$, OR = 1.45; 95% CI: 1.38, 1.52). Associations between moderate and extreme heat and admissions for all causes and cardiovascular and respiratory diseases were also significantly deleterious (OR > 1) for lags 0-1, and associations between heat and admissions were stronger for respiratory than cardiovascular causes (e.g., for respiratory admissions for $AT01_{EH}$, OR = 1.17; 95% CI: 1.13, 1.20). However,

at longer lags, associations between admissions and both moderate and extreme heat were significantly protective (OR < 1), with a protective effect evident out as far as lag 17-20. The sums of the individual lag periods from lag days 0-20 showed a protective effect of heat on hospital admissions for all causes, cardiovascular and respiratory admissions for both moderate heat and extreme heat (e.g., for the sum of extreme heat effects from lag days 0-20 for admissions for respiratory diseases, OR = 0.62; 95% CI: 0.59, 0.65). However, for admissions for renal diseases, the protective effects of moderate and extreme heat declined by lag day 16, and the 21-day sum of the extreme heat effects was still deleterious (OR = 1.15; 95% CI: 1.04, 1.27).

The added heat-wave effect, or the effect of consecutive days of extreme heat over and above the effect captured by the moderate heat term in the model, was significantly associated with admissions for renal diseases (for a heat wave defined as at least 8 consecutive days of extreme heat vs. extreme heat for less than 8 consecutive days, OR = 1.23; 95% CI: 1.10, 1.38) (Table III.2). However, for renal admissions, the sum of the independent effects and the added heat-wave effect (a heat wave defined as at least 8 days vs. only moderate heat for 8 days, OR = 1.47; 95% CI: 1.31, 1.67) was not significantly greater than the effect of extreme heat on lag days 0-1 (OR = 1.43; 95% CI: 1.37, 1.50). For cardiovascular and respiratory admissions, even after adding the heat-wave effect to the independent 2-day extreme heat effects, the ORs for 8-day durations of extreme heat were still less than the effect of extreme heat on lag days 0-1 and still significantly less than 1 (Table III.2). In other words, the effect of an 8-day heat wave was not higher than the effect of extreme heat on lag days 0-1 for any of the admissions causes, and even during a heat wave, the effect of extreme heat on cardiovascular and respiratory admissions was still protective.

Within each climate zone, for the associations between admissions for all, renal and respiratory diseases and extreme heat on lag days 0-1, the ORs were significantly greater than 1 except for climate zone 5 for respiratory diseases (Table III.3). For the sum of effects from lag days 0-7, extreme heat was protective in all climate zones for admissions for all causes and cardiovascular and respiratory diseases. For the sum of effects from lag days 0-7, extreme heat was still deleterious for admissions for renal diseases in each climate zone. For respiratory admissions, we found heterogeneity in effect estimates between climate zones as well as within climate zones for extreme heat over lag days 0-1 and lag days 0-7.

Results of Sensitivity Analyses

Confounding by ozone of the association between AT and hospital admissions was minimal. $AT01_{EH}$ from the models with ozone differed from those in the models without ozone by more than 10% (but less than 24%) in only 3 cities for renal admissions (results not shown). Confounding by holidays was also minimal. In models with terms for holidays vs. models without holiday terms, the ORs for moderate and extreme heat on lag days 0-1 as well as their sums over lag days 0-7 did not differ by more than 10%.

When we varied the length of the time stratum, the moderate and extreme heat effect estimates were similar for lag days 0-1 (see Appendix A, Figure A.2). For the sum of the effects over lag days 0-7, the effect estimates were higher in models with the shortest time strata (6 pseudo-months vs. 4 pseudo-months or 5 real months).

Different temperature metrics had similar associations between hospital admission for all natural causes and moderate heat on lag days 0-1, within each climate zone and overall (see Appendix A, Figure A.3A). However, associations between hospital admission and extreme heat on lag days 0-1 differed between metrics, with MA having a slightly stronger effect (OR for all

zones = 1.11; 95% CI: 1.10, 1.12) than AT, and DTR the weakest (OR for all zones = 1.04; 95% CI: 1.03, 1.05) (see Appendix A, Figure A.3B).

The effects of moderate and extreme heat on lag days 0-1 when extreme heat was defined as AT above the 95th percentile were similar to the effects when extreme heat was defined as being above the 90th percentile (see Appendix A, Figure A.3).

Effects of moderate heat estimated by more complex models, using data from April-October and incorporating terms for cold in addition to moderate heat and extreme heat (a double-threshold model with an indicator for extreme heat), were similar to effects estimated by the simpler model, which used data from May-September and only moderate and extreme heat terms (see Appendix A, Figure A.3). The SiZer method failed to identify distinct heat and cold thresholds (see Appendix A).

DISCUSSION

This large, multi-city study of heat, heat waves and hospital admissions among elderly Medicare beneficiaries suggests that morbidity related to hot weather presents an important health burden. With the frequency and intensity of hot weather predicted to increase over time and an aging population, these results have important implications for enhancing public health preparedness.

Extreme heat on the day of and the day before admission was strongly associated with hospitalizations for renal diseases. As ORs estimate incidence rate ratios in our study, for extreme heat, we found a 43% (95% CI: 37%, 50%) increase in hospital admission rates for renal disease on lag days 0-1. Additionally, excess admissions for renal diseases occurred even with increases in moderate heat. Positive associations between temperature, heat events and admissions for renal diseases have been reported in several other studies in the U.S. and elsewhere (Fletcher et al. 2012; Green et al. 2010; Hansen 2008; Knowlton et al. 2009; Kovats et al. 2004; Mastrangelo et al. 2006; Mastrangelo 2007; Nitschke et al. 2007; Nitschke et al. 2011; Semenza 1999; Wang et al. 2012). Renal admissions increased 8% (95% CI: 5%-12%) among individuals aged 65-84 in New York State for a 2.8 ºC increase in mean temperature (Fletcher et al. 2012). Among individuals 65 years and older, admissions for acute renal failure increased 11% (95% CI: 6%-15%) for a 5.6 ºC increase in AT in California (Green et al. 2010). During the 2006 heat wave in California, renal admissions increased 4% (95% CI: 1%-7%) (Knowlton et al. 2009). During the 1995 heat wave in Chicago, Illinois, renal admissions increased 109% (95% CI: 84%-140%) (Semenza 1999). This body of evidence suggests a need to target patients with renal conditions for additional protective measures during hot weather in cities across the U.S,

though individuals with previously identified renal conditions may not account for the entire increase in renal admissions associated with heat.

We found only a slight increase in hospital admissions rates for cardiovascular diseases with moderate heat (for a 1 °C increase in AT, < 0.5%) and extreme heat (1%) and a stronger association with admissions rates for respiratory diseases (0.5% and 14%, respectively) on lag days 0-1. Other studies of associations between cardiovascular and respiratory admissions and heat and heat waves in the U.S. have found increased risks of cardiovascular and respiratory diseases on lag days 0-1 (Ye et al. 2012). Studies using time series of admissions and temperature data from earlier time periods (e.g., Schwartz et al. 2004) tended to find stronger associations between cardiovascular admissions and heat than our study. These differences in results by time period may be related to the implementation of heat health warning systems in several U.S. cities and increased awareness of the dangers of heat to the elderly after the 1995 Chicago heat wave (Bassil 2011). More similar to our findings, a study in California from 1999-2005 (Green et al. 2010) and a study in New York State from 1991-2004 (Lin et al. 2009) did not find increases in cardiovascular hospital admissions rates with heat on lag days 0 or 1. In a meta analysis of the associations between heat and admissions for cardiovascular and respiratory diseases from studies worldwide, Turner and colleagues (2012) also did not find significant associations for cardiovascular admissions, though their results were suggestive of an association between respiratory admissions and heat (for a 1 °C increase in temperature, RR = 1.020; 95% CI: 0.986, 1.055).

The associations between cardiovascular hospital admissions and heat were weaker than between cardiovascular mortality and heat found in previous U.S. studies, but the associations between respiratory hospital admissions and heat were stronger than for respiratory mortality and

heat. We found a 1% (95% CI: 0%, 3%) increase in cardiovascular admissions and a 14% (95% CI: 11%, 17%) increase in respiratory admissions associated with extreme heat. In contrast, Anderson and Bell (2009) found a 5% increase in cardiovascular mortality and 6% increase in respiratory mortality among individuals 75 years and older for an increase in mean daily temperature from the 90^{th} to 99^{th} percentile on lag days 0-1. In the U.S., deaths associated with extreme heat were higher among individuals dying out-of-hospital as well as individuals dying of stroke or atrial fibrillation (Medina-Ramon et al. 2006), so heat may have a stronger association with cardiovascular mortality than hospital admissions because heat-related deaths may tend to be more sudden.

The associations between hospital admissions and moderate heat were weak (< 4% increase in admissions for an IQR increase in AT), but stronger for extreme heat (8% increase in admissions for extreme heat). Furthermore, the effects of extreme heat were similar regardless of whether extreme heat was defined as AT above the 90^{th} or 95^{th} percentile of AT, suggesting that the association between extreme heat and hospital admissions is driven by temperatures at or above the 95^{th} percentile.

Consistent with studies of the added heat wave effect in the association between heat and mortality (Anderson and Bell 2011, Gasparrini and Armstrong 2011), we did not see a substantial added heat wave effect for cardiovascular and respiratory admissions. In a multi-city U.S. study modeling temperature as a spline and heat wave as an indicator variable, Gasparrini and Armstrong (2011) found added heat wave effects from 0-7%, with the greatest added heat wave effect when the temperature spline had the fewest degrees of freedom. In our model, with temperature below a threshold treated as only a linear term, we still found only a small added heat wave effect of 1-3% for cardiovascular and respiratory diseases.

Although we found an added heat-wave effect in the association between heat and hospital admissions for renal diseases (for heat waves at least 8 days long, OR = 1.23, 95% CI: 1.10, 1.38), heat waves did not increase the risk of renal admission beyond that of extreme heat on lag days 0-1. However, even after accounting for displacement, or the harvesting effect, whereby the exposure advances a health outcome by only a few days because the affected individuals are already very frail (Schwartz et al. 2004), extreme heat was still associated with a significant decrease in admissions for renal disease over the 21-day period we analyzed. In contrast, for cardiovascular and respiratory admissions, the prior 8 days of exposure to extreme or moderate AT, even after accounting for an added heat-wave effect, were protective in sum (though the 8-day effect estimates were sensitive to the lengths of the time strata). Mortality displacement patterns have varied widely in studies of heat-associated cardiovascular and respiratory mortality in the U.S. and Europe with some studies finding the sum of effects over multiple lags to be deleterious (e.g., Braga et al. 2001, Hajat et al. 2005 for London respiratory diseases), not significantly different from the null (e.g., Baccini 2008) or protective (e.g., Hajat et al. 2005 for London cardiovascular diseases). Displacement may be more pronounced among heat-associated hospitalizations than mortality because it is likely easier for individuals to avoid hospitalization than to avoid death. The displacement effect found in an earlier multi-city U.S. study of heat and hospital admissions (Schwartz et al. 2004) was not as pronounced as that found in this study. Methodological differences may account for these differences; Schwartz and colleagues used a time series model and a more flexible distributed lag constraint. However, they also used an earlier data set (1984-1996), and as discussed above, individuals with cardiovascular and respiratory diseases may now receive better care in the days immediately following a period of extreme heat.

Nevertheless, when considering application of these results to heat health warning systems, our finding of important morbidity associations with heat in the short term (lags 0-1), even for cardiovascular and respiratory causes, suggests that mobilization of prevention programs and readying of hospitals and ambulance services prior to forecast periods of extreme heat is important to prepare for the short-term increased health burden during extreme heat. To further enhance our knowledge on what conditions should activate a heat health warning system and to gauge the relative importance of hospital admissions and mortality in identifying heat health effects, studies using identical methods to analyze the associations between heat and mortality and heat and morbidity are warranted.

The Energy Information Administration climate zones did not explain city-specific variation in the association between heat and admissions for respiratory diseases. Factors other than prevailing weather conditions, including vegetation, housing stock, access to air conditioning, and social factors may play important roles in determining the extent to which extreme heat puts the health of older people at risk in any given community, and using information on neighborhood of residence as well as city of residence, we are actively investigating characteristics of vulnerability to heat-associated hospital admissions.

CONCLUSION

The association between extreme heat and hospital admissions for all causes on lag days 0-1 was statistically and clinically significant in the U.S. in all climate regions. Elderly individuals with cardiovascular, respiratory and especially renal conditions, and providers of services to such people, may benefit from taking additional precautions when heat warnings are issued.

TABLES

Table III.1. Population-weighted means (and ranges) of hospital admissions among elderly Medicare beneficiaries, apparent temperature, heat waves and ozone, by climate zone, May-September, 1992-2006.

	Zone 1 (13 cities)	Zone 2 (34 cities)	Zone 3 (22 cities)	Zone 4 (24 cities)	Zone 5 (21 cities)	All Zones (114 cities)
Hospital Admissions (daily count)[a]						
all natural causes	53 (19-97)	241 (16-571)	266 (21-570)	142 (16-336)	98 (18-201)	186 (16-571)
cardiovascular	13 (5-24)	59 (4-133)	65 (5-135)	33 (4-77)	24 (4-53)	45 (4-135)
heat-related	0.0 (0.0-0.1)	0.2 (0.0-0.7)	0.3 (0.0-0.6)	0.1 (0.0-0.2)	0.1 (0.0-0.2)	0.2 (0.0-0.7)
renal	0.6 (0.2-1.2)	2.8 (0.1-6.0)	3.0 (0.2-6.2)	1.8 (0.1-4.1)	1.2 (0.2-2.0)	2.2 (0.1-6.2)
respiratory	5 (2-8)	21 (2-47)	22 (2-49)	13 (1-31)	8 (2-16)	16 (1-49)
25^{th}-75^{th}-90^{th}-95^{th} percentiles of AT01 (°C)[b]	14.3-23.2-26.3-27.9	16.2-25.3-28.5-30.0	18.8-27.0-29.8-31.2	20.0-24.7-26.7-27.8	29.4-33.8-35.0-35.6	20.0-27.2-29.6-30.9
Annual number of days in a heat wave (consecutive 2-day means each above 95th percentile of AT01) by heat-wave duration						
2-day	7.6 (7.3-7.9)	7.7 (7.1-8.1)	7.7 (7.1-7.8)	7.7 (7.4-8)	7.7 (7.4-7.9)	7.7 (7.1-8.1)
4-day	2.6 (1.8-3.4)	2.8 (2.3-3.7)	2.9 (2.3-4.7)	3.4 (2.2-4.3)	3.1 (2.4-4.0)	3.0 (1.8-4.7)
6-day	0.8 (0.2-1.2)	1.0 (0.3-2.3)	1.0 (0.3-3.1)	1.7 (0.5-2.6)	1.4 (0.5-2.7)	1.2 (0.2-3.1)
8-day	0.2 (0.0-0.6)	0.4 (0.0-1.4)	0.4 (0.0-2.1)	0.9 (0.0-1.7)	0.6 (0.1-2.2)	0.5 (0.0-2.2)
mean daily ozone (ppb)[c]	45 (37-49)	45 (36-54)	46 (33-56)	50 (27-71)	44 (29-57)	46 (27-71)

[a] ICD-9-CM Codes: all natural causes (all ICD-9-CM codes < 800), cardiovascular (390-429), heat (including 992 (effects of heat and light) and E900.0 (excessive heat due to weather conditions)), renal (580-589) and respiratory (480-487, 490-492 and 494-496). The "heat" category also includes admissions with any secondary causes related to heat.

[b] AT01 = 2-day mean of daily mean apparent temperature

[c] Number of cities contributing to ozone calculations: 11, 32, 22, 20 and 19 for zones 1-5, respectively.

Table III.2. Pooled odds ratios (95% confidence intervals) for the association between hospital admissions for different causes and different heat exposures.

	All causes	Cardiovascular	Renal	Respiratory
Sum of the independent effects of extreme heat[a]				
lag days 0-1[b]	1.08 (1.07, 1.09)	1.01 (1.00, 1.03)	1.43 (1.37, 1.50)	1.14 (1.11, 1.17)
lag days 0-3	1.02 (1.01, 1.03)	0.96 (0.95, 0.98)	1.35 (1.27, 1.43)	1.03 (1.00, 1.07)
lag days 0-5	1.00 (0.99, 1.01)	0.89 (0.88, 0.90)	1.29 (1.22, 1.37)	0.99 (0.96, 1.02)
lag days 0-7	0.94 (0.93, 0.95)	0.84 (0.82, 0.85)	1.28 (1.20, 1.37)	0.85 (0.82, 0.88)
added heat-wave effect for 3 heat-wave durations				
lag days 0-3	1.01 (1.01, 1.02)	1.01 (1.00, 1.02)	1.07 (1.02, 1.13)	1.03 (1.00, 1.05)
lag days 0-5	1.00 (1.00, 1.01)	1.01 (0.99, 1.03)	1.10 (1.02, 1.18)	1.03 (1.00, 1.07)
lag days 0-7	1.00 (0.98, 1.02)	1.01 (0.97, 1.06)	1.23 (1.10, 1.38)	0.98 (0.90, 1.07)
sum of the independent effects and the added heat-wave effect for 3 heat-wave durations[c]				
lag days 0-3	1.03 (1.02, 1.04)	0.98 (0.96, 0.99)	1.43 (1.35, 1.51)	1.05 (1.01, 1.09)
lag days 0-5	1.00 (0.99, 1.02)	0.90 (0.88, 0.92)	1.39 (1.28, 1.51)	1.01 (0.96, 1.06)
lag days 0-7	0.93 (0.91, 0.95)	0.85 (0.81, 0.89)	1.47 (1.31, 1.67)	0.80 (0.72, 0.89)

Example model terms (for model including added heat-wave effect for 6-day duration): $\beta_1 AT01_{MH} + \beta_2 AT01_{EH} + \beta_3 AT23_{MH} + \beta_4 AT23_{EH} + \beta_5 AT45_{MH} + \beta_6 AT45_{EH} + \beta_7 AT67_{MH} + \beta_8 AT67_{EH} + \beta_9 HW$,
where $AT01_{MH}$ = the mean over lag days 0 and 1 of daily mean apparent temperature (AT) below the 95th percentile,
$AT01_{EH}$ = the mean over lag days 0 and 1 of daily mean apparent temperature (AT) above the 95th percentile and
HW = the added heat-wave effect = $AT01_{EH} \cdot AT23_{EH} \cdot AT45_{EH}$

[a]Example sum (for 6 days, or over lag days 0-5): $e^{(\beta_2 + \beta_4 + \beta_6)}$

[b]from a model without the HW term

[c]Example sum (for 6-day duration): $e^{(\beta_2 + \beta_4 + \beta_6 + \beta_9)}$

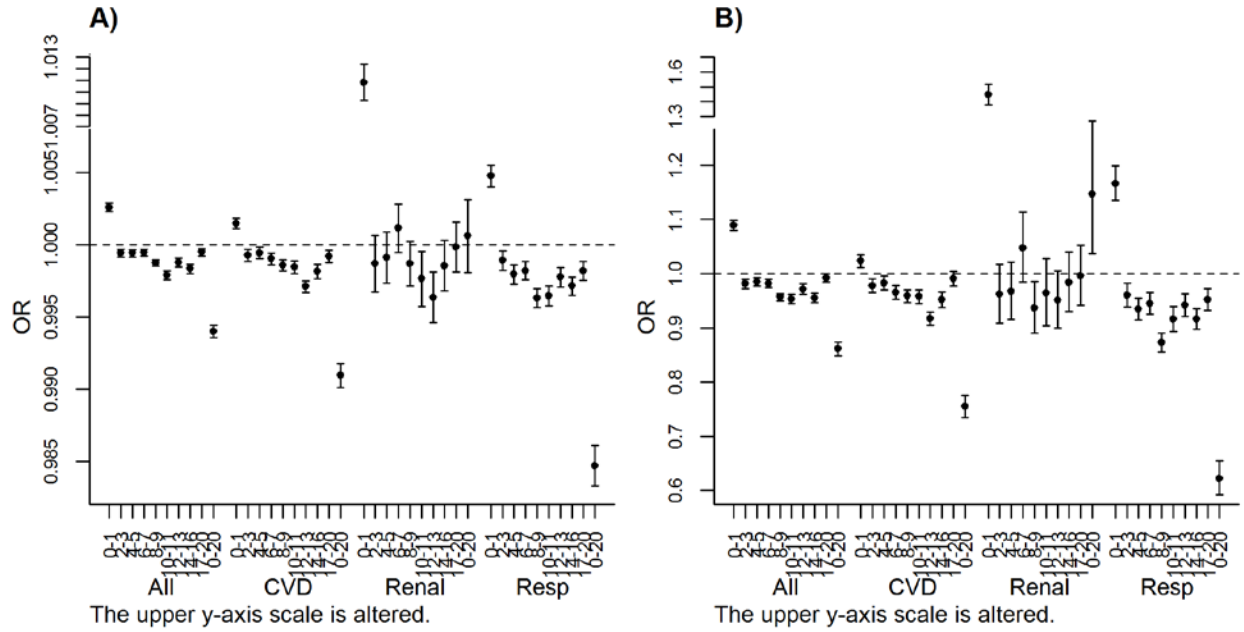
Table III.3. Odds ratios (95% confidence intervals) for hospital admission associated with extreme heat on lag days 0-1 and the sum of the extreme heat effects from lag days 0-7.[a]

Climate Zone	All causes	Cardiovascular	Renal	Respiratory
Extreme Heat on Lag Days 0-1				
1	1.09 (1.06, 1.11)	1.07 (1.03, 1.11)	1.51 (1.29, 1.77)	1.13 (1.03, 1.24)[b]
2	1.08 (1.07, 1.09)	1.01 (0.99, 1.02)	1.42 (1.31, 1.54)	1.18 (1.13, 1.22)[b]
3	1.07 (1.05, 1.09)[b]	1.01 (0.99, 1.03)	1.44 (1.32, 1.58)	1.09 (1.02, 1.16)[b]
4	1.11 (1.08, 1.14)[b]	1.01 (0.97, 1.05)	1.54 (1.31, 1.82)	1.16 (1.08, 1.25)
5	1.05 (1.01, 1.09)[b]	1.01 (0.96, 1.06)	1.40 (1.14, 1.72)	1.01 (0.93, 1.09)
all	1.08 (1.07, 1.09)[b]	1.01 (1.00, 1.03)	1.43 (1.37, 1.50)	1.14 (1.11, 1.17)[b,c]
Extreme Heat on Lag Days 0-7[d]				
1	0.96 (0.94, 0.98)	0.88 (0.84, 0.93)	1.16 (0.95, 1.41)	0.87 (0.78, 0.96)
2	0.94 (0.93, 0.96)	0.83 (0.81, 0.85)	1.29 (1.18, 1.40)	0.90 (0.86, 0.93)
3	0.94 (0.92, 0.96)	0.84 (0.80, 0.88)[b]	1.25 (1.08, 1.45)	0.82 (0.76, 0.88)[b]
4	0.96 (0.93, 0.99)	0.82 (0.77, 0.86)[b]	1.36 (1.13, 1.64)	0.86 (0.78, 0.94)
5	0.89 (0.86, 0.91)	0.84 (0.80, 0.89)	1.11 (0.89, 1.39)	0.73 (0.65, 0.82)
all	0.94 (0.93, 0.95)[c]	0.84 (0.82, 0.85)[b]	1.28 (1.20, 1.35)	0.85 (0.82, 0.88)[b,c]

[a]Extreme heat = 2-day mean of daily mean apparent temperature above the 95th percentile ($AT01_{EH}$)
[b]Significant heterogeneity within climate zone category ($p < 0.05$ in Q test for heterogeneity).
[c]Significant heterogeneity between climate zones 1-5 ($p < 0.05$ in Q test for heterogeneity).
[d]Results sensitive to length of time strata for all-causes, cardiovascular and respiratory. See Appendix A, Figure A.2B.
City-specific results available upon request.

FIGURES

Figure III.1. Odds ratios (ORs) and 95% confidence intervals (CIs) for all cities for the increase in hospital admissions among U.S. elderly (May-September, 1992-2006) for each multi-day mean (lag days 0-1, 2-3, 4-5, 6-7, 8-9, 10-11, 12-13, 14-16, 17-20) and the sum of lags 0-20 for (A) moderate heat (1 ºC increase in 2-day mean daily mean apparent temperature (AT) below the 95th percentile of 2-day mean AT), and (B) extreme heat (2-day mean AT above the 95th percentile).



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CHAPTER IV

Vulnerability to Heat-Associated Hospital Admissions Among the Elderly in the United States by Individual and Area-Level Characteristics, 1992-2006

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Abbreviations and Definitions:
AC: air conditioning
admissions displacement: when the sum of the effects of the exposure over longer lags are reduced because the exposure advanced the admissions of already frail individuals by only a few days
CI: confidence interval
EH: extreme heat
EH01: extreme heat over lag days 0-1, or an indicator variable taking the value of 1 if the mean of daily maximum temperature over lag days 0-1 (the day of and day before a hospital admission) is above the city-specific percentile threshold, i.e., the 95th percentile of warm-season (May-September) 2-day means of daily maximum temperatures
EH07: extreme heat over lag days 0-7
MH01: moderate heat, or the mean of daily maximum temperature, in °C, over lag days 0-1 (the day of and day before a hospital admission) taking a value of 0 above the city-specific percentile

threshold, i.e., the 95th percentile of warm-season (May-September) 2-day means of daily maximum temperatures
MH07: moderate heat over lag days 0-7
ICD-9-CM: The International Classification of Diseases, Ninth Revision, Clinical Modification
IQR: Interquartile range
OR: odds ratio
TMAX: daily maximum temperature
ZCTA: ZIP Code Tabulation Area, or polygon constructed by the U.S. Census Bureau approximating a ZIP code, which is not necessarily a true polygon

ABSTRACT

Background: With extreme heat (EH) events expected to increase with climate change, it is important to understand which populations are vulnerable to health effects of heat for targeted interventions.

Objectives: To determine whether the associations between EH and hospital admissions for renal, heat and respiratory diseases are modified by individual and ZIP-code level characteristics, and citywide air conditioning (AC) prevalence among individuals aged 65 years or older in 134 U.S. cities, May-September, 1992-2006.

Methods: We used data from Medicare billing records, airport weather monitors, the U.S. Census, the National Land Cover Dataset, and air quality monitors in a time-stratified case-crossover design with interaction terms between EH and both individual (age, race, sex) and ZIP-code level (non-green space, high school degree, nonwhite race, poverty) characteristics in a single model. We then regressed the city-specific EH effect estimates on AC prevalence.

Results: Age > 78 years; low education and high nonwhite race in a ZIP code; and low AC prevalence increased the association between EH and hospital admissions (e.g., during EH, 14% (95% CI = 5%, 24%) increase in odds of admission for an interquartile range increase in percent of residents without a high school degree in a ZIP code), and lower education and AC prevalence had a stronger modifying effect over the longer period of 0-7 days after admission. Individual-level race did not modify EH effects, but results suggested a modifying effect of non-green space. Significant heterogeneity existed between cities for most of the modifying characteristics examined.

Conclusion: Older people and those living in areas with: more residents with lower education and of nonwhite race; and lower AC prevalence, are more vulnerable to hospitalization during

EH in the U.S. These subgroups should be considered in burden of disease estimates, heat health warning systems and adaptation measures, taking into account the vulnerability differences observed among cities.

BACKGROUND

Over the 21st century, temperature extremes and extreme heat (EH) episodes are very likely to increase (IPCC 2007). Understanding of the present and future health burden of heat and who is most vulnerable to the effects of heat is needed to adapt to climate change.

The association between heat and mortality is well studied across a wide variety of climates, with stronger associations found in cities with lower air conditioning (AC) prevalence (Hajat and Kosatsky 2010). A smaller number of studies have examined associations between heat and morbidity outcomes, such as hospital admissions, ambulance dispatches or emergency room visits for heat stroke, heat exhaustion, fluid and electrolyte abnormalities, renal failure, cardiovascular disease and respiratory disease, with mixed results (Bhaskaran 2009; Turner et al. 2012; Xu et al. 2012; Ye et al. 2012). A meta-analysis of hospital admissions for cardiovascular and respiratory diseases suggested an association between respiratory admissions and heat but not between cardiovascular admissions and heat (Turner et al. 2012). More recently, a study of 114 cities across the United States found a 43% (95% CI: 37%, 50%) increase in admissions for renal diseases, a 1% (95% CI: 0%, 3%) increase in admissions for cardiovascular diseases and a 14% (11%, 17%) increase in admissions for respiratory diseases with EH on lag days 0-1 (EH01, extreme heat on the day of and the day before hospital admission). However, this study found substantial displacement of cardiovascular and respiratory admissions ("admissions displacement"), in which effects of EH at longer lags were reduced. This is possibly because EH had advanced the admissions of these already frail individuals by only a few days; consequently, in the days following EH, a significant decline in the rate of hospital admissions for cardiovascular and respiratory diseases was observed (Gronlund et al. 2013).

Individual-level or area-level characteristics which increase vulnerability to heat-associated morbidity have also been evaluated in previous studies, although the methods and results have varied widely. The researchers evaluated these characteristics as either 1) predictors of heat-related illnesses such as heat stroke or 2) effect modifiers of the association between heat and other morbidity outcomes (either by stratifying the analysis by the effect modifier, using the effect modifier as an outcome variable in a meta-analysis of main effects of temperature or by including an interaction term between the main effect and the effect modifier in the model). Using the first design to address effect modification, in the summer of 2005 in Phoenix, AZ, the following census block group characteristics were independently associated with the occurrence of any heat distress calls in a census block group: maximum nighttime surface temperature, percent impervious surface, housing density, population aged 65 or older, percent people living alone, percent of households linguistically isolated, percent black race, percent Hispanic, percent Asian, percent of households vacant, and population size (Uejio et al. 2011). Several studies have used the second design. A California study found that age and race modified heat associations with emergency department visits for cardiovascular and respiratory diseases, diabetes, heat illness, intestinal infections and acute renal failure during the summers of 2005-2008, although the direction of the effects varied depending on the disease type (Basu et al. 2012). In a study of hospital admissions for acute renal failure in New York State, 1991-2004, Fletcher and colleagues found effect modification by race and ethnicity, but not by age, sex, income or region (Fletcher et al. 2012). Using information from a California residential survey of AC prevalence and use, a 0.55% reduction in risk of respiratory hospitalization per 10 °F increase in AT was seen per 10% increase in central AC use in a given area (Ostro et al. 2010). Summarizing findings on vulnerability to heat is challenging since many studies report estimates of the effects

of heat on morbidity outcomes stratified by potential characteristics of vulnerability, but do not quantitatively evaluate whether these effect estimates differ significantly between strata.

In this study, we addressed two main questions: (1) Do individual-level characteristics age, race and sex as well as the ZIP-code (postal code) level characteristics of non-green space, education, race and poverty modify the association between EH and hospital admissions for respiratory and for renal and heat-related causes in the United States from 1992-2006, controlling for confounding between the potential effect modifiers? (2) Does AC prevalence in a city modify the main effect of, as well as the individual and ZIP-code level effects on the association between, EH and hospital admissions? We evaluated the effect modification over both the very short-term (EH 0-1 days prior to admission) and the longer term (EH 0-7 days prior to admission) to understand how the previously observed patterns of admissions displacement (Gronlund et al. 2013) might differ within vulnerable subpopulations.

METHODS

Study cities and regions

The 200 counties in the continental United States with the highest number of cardiovascular hospital admissions in 2004-2006 were assigned to their respective Metropolitan Statistical Areas to form the study cities, as previously described (Gronlund et al. 2013; Zanobetti et al. 2012).

Health outcomes

We obtained emergency hospital admissions for individuals 65 years and older during1992-2006 from the U.S. Centers for Medicare and Medicaid Services MedPAR billing records. These records contained the sex, race and age of the patients, which we further categorized as female vs. male, white vs. nonwhite race, and aged 65-78 years vs. aged 78 years and older. We categorized admissions with the primary admission International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes of 580-589 (renal), 992 (effects of heat and light) and E900.0 (excessive heat due to weather conditions) as "renal/heat." In previous analyses, we found a pronounced admissions displacement effect for admissions for respiratory causes, whereby the sum of the effects of EH on lag days 0-1 through lag days 6-7 was protective. Therefore, we categorized respiratory admissions separately (ICD-9-CM codes 480-487, 490-492 and 494-496). The "heat" category also included secondary causes of admission related to heat. The research was approved by the Institutional Review Boards at Harvard University and University of Michigan.

Temperature

We obtained daily maximum temperature for each city from the National Climatic Data Center Cooperative Summary of the Day station files (National Climatic Data Center 2010a). Data from a single monitor for each city were used except in 6 cities where multiple observations were missing from all the nearby monitors, in which case hourly data from the National Climatic Data Center's Integrated Surface Database Lite (National Climatic Data Center 2010b) were converted to daily values. All cities had daily maximum temperature measurements on at least 15% of the study days, which were the days of the warm season (May-September), 1992-2006.

Area-Level Characteristics

We obtained neighborhood-level socio-demographic characteristics from Decennial Census Long Form data in 2000 ZIP Code Tabulation Areas (ZCTAs, polygons constructed by the U.S. Census Bureau approximating ZIP codes, which are not true polygons), for 1990 and 2000 (2006). ZCTAs were included in the study cities if a portion of the ZCTA lay within a study county. We extracted the following characteristics for each study ZIP code: percent nonwhite, percent without a high school degree and percent of households at or below the poverty level.

Land cover classifications at a resolution of 30 x 30 m were obtained from the Multi-Resolution Land Characteristics Consortium for 1992 and 2001 (U.S. Department of the Interior 2007). We further classified these data as "green space" vs. "non-green space" and calculated the percent area non-green space in each ZIP code using ZCTA 2000 Census TIGER/Line shapefiles as was done previously by census tract (Reid et al. 2009).

We obtained citywide central AC prevalence for 109 study cities from 1985-2005 from the American Housing Survey (U.S. Census Bureau 2008). We applied the corresponding Metropolitan Statistical Area prevalence when the county prevalence was not available.

We estimated annual values for land cover and socio-demographic characteristics for each ZIP code and city as the value from the nearest year of available data.

Statistical Analysis

We used a time-stratified case-crossover design as previously described (Medina-Ramon and Schwartz 2007) to evaluate the association between heat and hospital admissions in each city using data on hospital admissions occurring from May through September. Control days were chosen such that cases and controls were matched on calendar month and day of week. We applied conditional logistic regression using the coxph package in R.

We modeled temperature as a step function, with steps at the city-specific 0-90th percentiles of 2-day mean TMAX, 90th-97th percentiles (moderate heat, MH) and above the 97th percentiles (EH). Percentiles of TMAX were calculated with respect to temperatures over the entire study period. We modeled temperature as a step function instead of a continuous function because this allowed us to restrict our data sets to "discordant sets," or matched sets of cases and controls where the exposures differed between the case and controls, which made it possible to analyze the largest cities. (In matched designs, only the discordant sets contribute information.) We modeled temperature exposure as 2-day means of lags to reduce collinearity between temperature lags in the models and to reduce the number of model terms (Armstrong 2006). Specifically, we used the following lags for MH and EH: 0-1 (the day of and day prior to the hospital admission), 2-3, 4-5, and 6-7 (for 2 and 3, 4 and 5, and 6 and 7 days before hospital admission, respectively). We created interaction terms between each of the 4 EH lags and the

effect modifiers of interest. For each city and each cause of admission (renal/heat or respiratory), in addition to parameters for each matched set of cases and controls which were conditioned out of the likelihood function, the model included the following terms:

$$\text{logit(hospital admission)} = \beta_1 MH01 + \beta_2 MH23 + \beta_3 MH45 + \beta_4 MH67 + \beta_5 EH01 + \beta_6 EH23 + \beta_7 EH45 + \beta_8 EH67 + \beta_9 EH01 \times EM_1 + \beta_{10} EH23 \times EM_1 + \beta_{11} EH45 \times EM_1 + \beta_{12} EH67 \times EM_1 + \ldots + \beta_{33} EH01 \times EM_7 + \beta_{34} EH23 \times EM_7 + \beta_{35} EH45 \times EM_7 + \beta_{36} EH67 \times EM_7 \quad [1]$$

where EM_1-EM_3 were indicator variables for sex, race (white vs. nonwhite) and age (65-78 vs. 79 years or older), respectively, and EM_4-EM_7 were percentages of non-green space, residents without a high school degree, residents of nonwhite race and residents below the poverty level in a ZIP code, respectively. EM_4-EM_7 were centered around the 25th percentile value of the respective modifier. This allowed the "reference category" to be white females aged 65-78 years in ZIP codes in the 25th percentile of percentages of non-green space, residents without a high school degree, residents of nonwhite race and residents below the poverty level, and β_5 through β_8 estimated effects for EH vs. non-EH in the reference category.

To estimate pooled effects across cities, heterogeneity within cities and evaluate whether city-level AC prevalence modified individual- and ZIP code level modifiers, we modeled city-specific model coefficients or sums of city-specific model coefficients in second stage random effect meta analyses against a random effect for city and either 1) an intercept (thereby pooling the effects using inverse-variance weights) or 2) an intercept and city-level predictor (i.e., AC prevalence) (Berkey et al. 1995). For each cause of admission, we pooled the coefficient for the main EH effect, the coefficient for the effect modifier of interest for the lag 0-1 coefficients (e.g., β_9 in equation 1) and the sum of the coefficients for lags 0-7 (e.g., sum of β_9 through β_{12} in equation 1) in a separate model for each sum. Between-city heterogeneity was assessed with the

Q test for heterogeneity. Additionally, these effects were each regressed against the citywide percent of households with central AC in 1999 (centered around the 25th percentile of AC prevalence). Meta-analyses were performed using the mvmeta package in R 2.15 (R Development Core Team 2013).

We present the interaction effect only (the added effect of a unit increase of the subgroup characteristic during EH) for the sociodemographic variables, rather than the sum of the main and interaction effects (the effect of EH vs. non-EH within a subgroup). We included multiple effect modifiers within a single model, and the large number of combinations of subgroups (e.g., older individuals residing in ZIP codes with high percentages of non-green space and residents without a high school degree) makes presentation of all possible combinations unwieldy. Furthermore, one cannot include non-time varying main effects (e.g., sex) in a conditional logistic regression model because they do not vary between the case and controls in each matched set. Therefore, by including multiple effect modifiers in a single model, we are left with only a single "reference category," which in this case is white women 65-78 years of age residing in the ZIP codes in the 25th percentile of: percent non-green space; percent of residents without a high school degree; percent of residents who are nonwhite and percent of residents living below the poverty level. The main EH terms of the model represent the effects of EH versus non-EH days among this group. Given these limitations, we believe the "added effects" of each subgroup to be more interpretable and do not sum the subgroup effects for single or multiple combinations of categories.

RESULTS

Individual, ZIP code and city characteristics

The 134 study cities were broadly distributed across the United States (Figure IV.1). The mean daily number of admissions in a city for renal/heat causes ranged from 0.1 to 6.8 and from 1.0 to 49.0 for respiratory causes (Table IV.1). Both distributions were skewed left, with median city values of 0.5 and 3.5 admissions, respectively. The percent of admission cases aged over 78 years ranged from 36.4% to 60.4% and the percent of male cases ranged from 39.2% to 51.6% across cities. The percent of cases of nonwhite race ranged widely across cities, from 3.6% to 47.2%. The distribution of the city-specific EH thresholds, or 97th percentile of 2-day average of maximum daily temperatures, was skewed left with a range of 21.7-38.8 °C and a median of 27.4 °C. The 4 ZIP code characteristics, percentages of non-green space, nonwhite, without a high school degree and below the poverty level, ranged from 0-100%, but the distributions of the 4 characteristics across the 8,200 ZIP codes were skewed left, with median values less than 50%. The median citywide percent of households with central AC in 1999 was 63.6%.

Effect modification by individual and ZIP-code characteristics and AC

The number of renal/heat and respiratory cases during EH days was insufficient to perform the analyses in 16 and 3 cities, respectively. When the model results were pooled across the cities, the odds of admission to the hospital for renal/heat causes during EH01 vs. non-EH01 was significantly greater than 1 in the reference category, (white females aged 65-78 years residing in the ZIP codes in the 25th percentile of percent non-green space, percent of residents without a high school degree, percent of residents who are nonwhite and percent of residents living below the poverty level) (OR = 1.23, 95% CI = 1.13, 1.35) (Table IV.2). The 2

characteristics: age greater than 78 years and an IQR increase in percent of residents in the ZIP code without a high school degree, both modified the association between admissions for renal/heat causes and EH01. The increased odds of admission to the hospital during EH01 for these 2 characteristics were 1.13 (95% CI = 1.07, 1.19) and 1.14 (95% CI = 1.05, 1.24), respectively. For renal/heat causes of admission, the association between EH07 (EH over lag days 0-7) and hospital admission was decreased and confidence intervals wider in the reference category (OR = 1.19, 95% CI = 1.02, 1.39). However, the modifying effect of age greater than 78 years persisted (OR = 1.16, 95% CI = 1.04, 1.30) and the modifying effect of percent of residents without a high school degree was increased (OR = 1.43, 95% CI = 1.23, 1.67).

For admissions for respiratory causes, the odds of admission during EH01 vs. non-EH01 were protective in the reference category (OR = 0.96, 95% CI = 0.93, 0.99) (Table IV.2). The characteristics male and age > 78 years significantly increased this association, and the increased odds of admission to the hospital during EH for these 2 characteristics were 1.03 (95% CI = 1.01, 1.05) and 1.03 (95% CI = 1.01, 1.05), respectively. The OR for percent non-green space was suggestive of an added effect (OR = 1.03, 95% CI = 0.99, 1.07, $p < 0.10$). For respiratory causes, the effect of EH07 vs. non-EH07 in the reference category was also less than 1, but percent of residents of nonwhite race increased this association (OR = 1.04, 95% CI = 1.00, 1.08), and the OR for percent of residents without a high school degree was suggestive of effect modification (OR = 1.04, 95% CI = 0.99, 1.09, $p < 0.10$).

When accounting for citywide AC prevalence in models without individual or ZIP code level modifiers, AC prevalence substantially modified the association between EH01 and EH07 and renal/heat and respiratory causes (Table IV.3). In cities with lower AC prevalence, the association between EH07 and respiratory admissions remained deleterious (for cities in the 25th

percentile of AC prevalence, OR = 1.07, 95% CI = 1.04, 1.10) as compared to cities with higher AC prevalence in which the association became null (for cities in the 75th percentile of AC prevalence, OR = 1.00, 95% CI = 0.97, 1.03). However, there was significant between-city heterogeneity in these estimates.

Citywide AC prevalence modified the association between admissions for respiratory causes and EH01 among the reference individuals. The OR for this association among cities in the 25th percentile of AC prevalence was 0.99 (95% CI = 0.95, 1.02) while the OR among cities in the 75th percentile was protective (OR = 0.92, 95% CI = 0.88, 0.97) (Figure IV.2). For EH07 for respiratory causes among the reference individuals, the OR for AC prevalence was suggestive of a modifying effect. However, AC prevalence did not modify the added effects of any of the individual or ZIP-code level characteristics, with the exceptions of a possible modifying effect by AC prevalence on the added effect of male sex on the association between EH01 and EH07 and admission for heat/renal causes and the added effect of percent of residents of nonwhite race on the association between EH01 and admission for respiratory causes.

We saw neither a modifying effect of percent non-green space or a modifying effect of AC prevalence on the effect of percent non-green space. However, an IQR increase in percent non-green space among cities in the 25th percentile of AC prevalence did increase the association between EH01 and renal/heat admissions (OR = 1.11, 95% CI = 1.00, 1.24) (Figure IV.2). In the association between respiratory admissions and EH01, percent non-green space was deleterious among cities in the 75th percentile of AC prevalence. Similarly, in the association between renal/heat admissions and EH01, for male sex, the added effect among cities in the 25th percentile of AC prevalence was protective, though we did not have evidence of an interaction

by sex. Also, in the association between respiratory admissions and EH07, percent of residents without a high school degree was protective among cities in the 25th percentile of AC prevalence.

Even after accounting for AC prevalence, we found significant heterogeneity in our effect estimates for the association between hospital admissions for renal/heat causes and EH01 vs. non-EH01 (Figure IV.2 and Appendix B, Figure B.1). Nevertheless, within these categories of effect modifiers, few, if any, cities had significant effects in the opposite direction of the meta-analysis effect (Appendix B, Figure B.1A-D). One exception was the added effect of EH07 and percent of residents below the poverty level in a ZIP code on the association between renal/heat admissions and EH, whereby the interaction effect was significantly protective in Philadelphia, PA, New York City, NY, Baltimore, MD, St. Louis, MO, Atlantic City, NJ and Charleston, SC (Appendix B, Figure B.1E). Another exception was the added effect of EH01 and percent of residents of nonwhite race in a ZIP code on the association between respiratory admissions and EH, whereby the interaction effect was significantly protective in Bergen-Passaic, NY, Los Angeles, CA and Oakland, CA (Appendix B, Figure B.1F).

DISCUSSION

The association between admissions for renal/heat causes and extreme heat was greater for individuals older than 77 years, and among individuals living in ZIP codes with an IQR (16.3%) increase in percent of residents without a high school degree. These added risks were significant over both the short term (lag days 0-1) and the longer term (lag days 0-7). Male sex and age modified the association between respiratory admissions and extreme heat over lag days 0-1, as well. Finally, an IQR increase in percent of residents of nonwhite race significantly increased the risk of hospital admission for respiratory causes over lag days 0-7. These findings suggest that in general, age, sex and ZIP-code level education are relevant characteristics of vulnerability to heat-associated admissions in the short term, and that age, ZIP-code level education and ZIP-code level race are important over the longer term. The short-term effects are relevant to hospitals which may have to contend with additional staffing and resource costs due to hospital admissions immediately following extreme heat episodes, while longer term effects which account for admissions displacement are relevant to burden of disease estimates as well as estimates of increased costs of hospitalization due to extreme heat. Measures targeting the very old as well as individuals residing in areas with lower levels of education may reduce the immediate as well as long-term burden of extreme heat, and estimates of the effects of heat on hospital admissions within specific categories of age, ZIP-code level education and ZIP-code level race may aid in calculating more refined burden of disease estimates.

Despite having only a very spatially coarse way to measure the potential influence of AC on the associations between EH and hospital admissions, we found that citywide AC prevalence did modify the association between extreme heat and hospital admissions. Furthermore, the admissions displacement observed in cities with high AC prevalence among respiratory

admissions was not observed in cities with low AC prevalence. However, AC prevalence did not modify the added effects of sociodemographic characteristics, except that among the reference individuals, higher AC prevalence was associated with an increasingly protective association between EH and respiratory admissions.

Having identified general trends, we note the large amount of between-city heterogeneity in the effect estimates, even after accounting for citywide AC prevalence. Therefore, we suggest that city-level results should be considered in many cases when identifying characteristics of vulnerability. For many of the sociodemographic characteristics, few, if any, cities had significant effects in the direction opposite of the meta-analysis effect. We thus conclude that the meta-analysis results were at least indicative of the direction of effect (protective or deleterious) for most or all of the cities. Notable exceptions were percent of residents below the poverty level in a ZIP code (in the association between EH07 and renal/heat admissions) and percent of residents of nonwhite race in a ZIP code (in the association between EH01 and respiratory admissions), which sometimes had significant protective and sometimes had significant deleterious effects, depending on the city. The category “nonwhite” is very broad, and the wide variety of cultural practices, English language proficiency, community cohesion and other neighborhood-level social factors represented among nonwhite races may affect vulnerability to heat differentially.

Percent non-green space in a ZIP code did not significantly modify the association between EH and admissions for renal/heat causes, though there was suggestion of a modifying effect of percent non-green space on the association between EH01 and respiratory admissions (3%, 95% CI = -1%, 7%). ZIP-code wide green space may be too coarse a measure covering too broad an area to observe the potential benefits of green space on reducing heat-associated

morbidity. In comparison, using data aggregated at the census block group (a smaller area) in Phoenix, AZ, Uejio and colleagues found associations between heat distress emergency calls and satellite-derived nighttime surface temperature, percent impervious density and housing density, all of which are correlated with green space (Uejio et al. 2011). Also, the ZIP-code level measures of education and poverty did not have individual-level information and may be serving as a proxy for individual-level or smaller-area level information.

Individual-level nonwhite race did not modify the association between extreme heat and hospital admissions in any of the models, and no significant heterogeneity was seen between cities in individual-level nonwhite race interaction effects. Therefore, when controlling for other potential effect modifiers, we did not find evidence that race at the individual level was a significant characteristic linked with vulnerability to heat-associated hospital admissions. Finally, we used very broad categories of admissions; we collapsed heat and renal admissions into one category and combined all respiratory admissions into another category. Basu and colleagues (Basu et al. 2012) found that the modifying effects of race and age on the association between heat and emergency room visits differed by finer disease subgroups, and the extent to which sociodemographic and land cover characteristics as well as air pollution levels modify the associations between heat and more specific causes of hospital admissions also deserve further research.

CONCLUSION

Age, sex, ZIP-code level education and race, and AC prevalence modified the association between extreme heat and hospital admissions for renal/heat and/or respiratory causes, and lower education and AC prevalence also were associated with reduced admissions displacement. Our results were suggestive of a modifying effect of non-green space, which is a more easily modifiable risk factor than the sociodemographic characteristics examined. Significant heterogeneity existed between cities for most of the modifying characteristics examined, and estimates of the short-term and longer-term costs of EH on hospital admissions as well as heat health warning systems and measures targeting vulnerable individuals should account for differences in characteristics of vulnerability between cities.

TABLES

Table IV.1. Characteristics of patients 65 years and older admitted to the hospital, maximum temperature, and ZIP code characteristics in 134 U.S. cities and 8,200 ZIP codes, May-September, 1992-2006.

	Minimum	25th percentile	Median	75th percentile	Maximum
Citywide mean daily number of hospital admissions[1]					
Renal/heat	0.1	0.3	0.5	1.0	6.8
Respiratory	1.0	2.2	3.5	6.3	49.0
Patient characteristics (citywide percent of respiratory, renal and heat cases)					
Aged > 78 years	36.4	46.1	49.3	51.1	60.0
Male	39.2	43.9	45.6	47.6	51.6
Nonwhite race	3.6	12.8	18.4	26.4	47.2
Citywide extreme heat threshold (97th percentile of 2-day average of maximum daily temperature, °C)	21.7	24.9	27.4	31.3	38.8
ZIP code characteristics (percent in ZIP code)					
Non-green space	0.0	10.0	38.6	73.9	100.0
Residents without a high school degree	0.0	9.8	16.4	26.1	100.0
Residents of nonwhite race	0.0	4.3	12.3	30.8	100.0
Residents below poverty level	0.0	4.2	7.5	14.4	100.0
Citywide percent of households with central air conditioning[2]	4.9	33.1	63.6	81.0	96.4

[1] ICD-9-CM primary admission codes: renal/heat: 580-589, 992 or E900.0; respiratory: 480-487, 490-492, 494-496. Counts of admissions for heat causes also include admissions with any contributing causes coded as heat-related.
[2] N = 109 cities, year = 1999.

Table IV.2. Pooled odds ratios (95% confidence intervals) for admission to the hospital for renal/heat causes or respiratory causes among individuals aged 65 years and older during extreme heat on lag days 0-1 or over lag days 0-7 (1) vs. non-extreme heat among "reference individuals" (white females aged 65-78 years residing in the ZIP codes in the 25th percentile of percent non-green space, percent of residents without a high school degree, percent of residents who are nonwhite and percent of residents living below the poverty level), (2) for the added effect during extreme heat for males vs. females, nonwhites vs. whites, ages 79 years or older vs. ages 65-78 years or (3) for the added effect during extreme heat for interquartile range increases in the percentages of non-green space, residents without a high school degree, nonwhite residents and residents below the poverty level in a ZIP code, May-September, 1992-2006.

Characteristic	Renal/heat lag days 0-1	Renal/heat lag days 0-7	Respiratory lag days 0-1	Respiratory lag days 0-7
Extreme heat vs. non-extreme heat among reference individuals	1.23 (1.13,1.35)	1.19 (1.02,1.39)	0.96 (0.93,0.99)	0.93 (0.89,0.98)
Male	0.96 (0.91,1.01)	0.91 (0.82,1.00)	1.03 (1.01,1.05)	1.01 (0.98,1.05)
Nonwhite race	1.02 (0.95,1.09)	0.98 (0.85,1.14)	1.02 (0.98,1.06)	0.97 (0.91,1.03)
Age > 78 years	1.13 (1.07,1.19)	1.16 (1.04,1.30)*	1.03 (1.01,1.05)	1.03 (0.99,1.07)
Percent non-green space	1.07 (0.98,1.16)	1.05 (0.91,1.21)	1.03 (0.99,1.07)	1.02 (0.97,1.08)
Percent residents without high school degree	1.14 (1.05,1.24)*	1.43 (1.23,1.67)*	1.02 (0.99,1.05)	1.04 (0.99,1.09)
Percent nonwhite residents	0.97 (0.92,1.03)	1.04 (0.94,1.16)*	1.01 (0.98,1.04)*	1.04 (1.00,1.08)
Percent residents below poverty level	1.03 (0.95,1.11)	0.98 (0.84,1.13)*	1.00 (0.98,1.03)	1.00 (0.96,1.05)

p-value for between city-heterogeneity: * $p < 0.05$. See Appendix B Figure B.1 for forest plots (city-specific results).

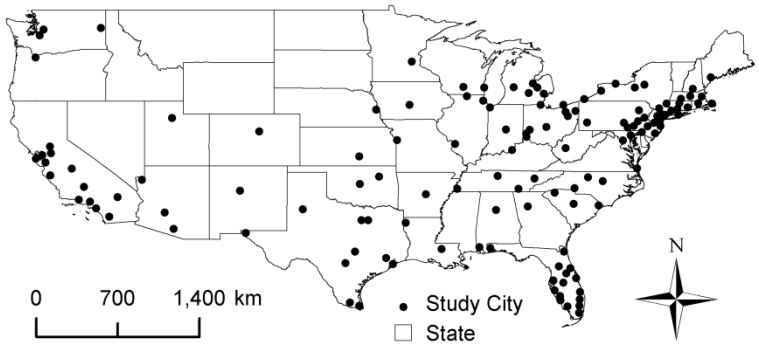
Table IV.3. Pooled odds ratios (95% confidence intervals) for admission to the hospital for renal/heat causes or respiratory causes among individuals aged 65 years and older for extreme heat vs. non-extreme heat on lag days 0-1 and summed over lag days 0-7 among cities in the 25th percentile of air conditioning (AC) prevalence and the 75th percentile of AC prevalence.

	Renal/heat	Respiratory
Extreme heat vs. non-extreme heat on lag days 0-1		
25th percentile of AC prevalence	1.58 (1.48,1.69)**#	1.07 (1.05,1.08)**#
75th percentile of AC prevalence	1.35 (1.26,1.45)**#	1.01 (0.99,1.03)**#
Extreme heat vs. non-extreme heat over lag days 0-7		
25th percentile of AC prevalence	2.00 (1.76,2.27)**#	1.07 (1.04,1.10)**#
75th percentile of AC prevalence	1.68 (1.48,1.91)**#	1.00 (0.97,1.03)**#

p-value for AC interaction term: * < 0.1, ** < 0.05.
p-value for between-city heterogeneity: # < 0.05.

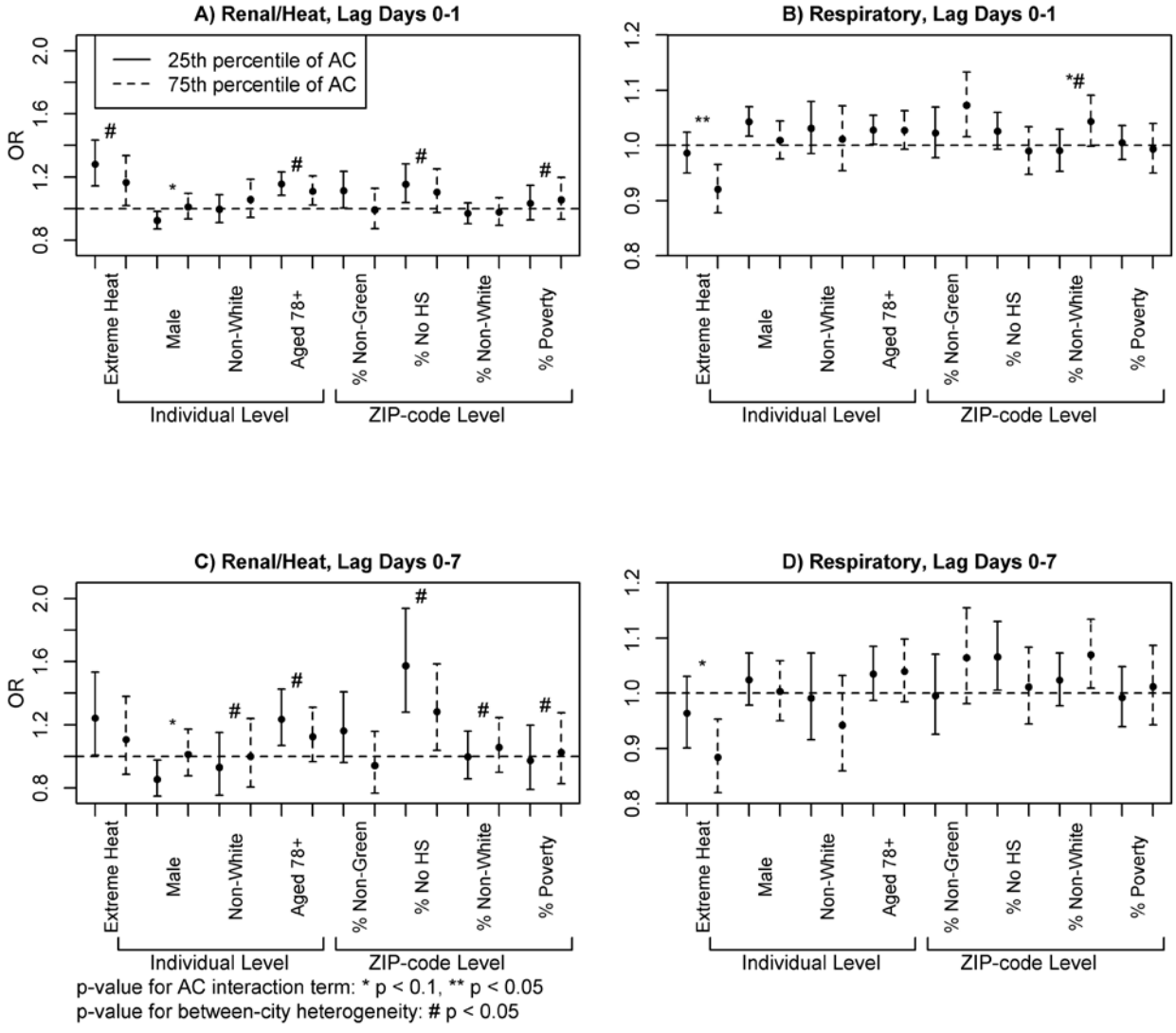
FIGURES

Figure IV.1. Study cities (n = 134) in the Continental United States.



Akron, OH
Albuquerque, NM
Allentown-Bethlehem, PA
Atlanta, GA
Atlantic City, NJ
Austin, TX
Bakersfield, CA
Baltimore, MD
Barnstable-Yarmouth, MA
Baton Rouge, LA
Bergen-Passaic, NJ
Birmingham, AL
Boston, MA
Brownsville, TX
Buffalo, NY
Canton-Massillon, OH
Charleston, WV
Charlotte, NC
Chattanooga, TN
Chicago, IL
Cincinnati, OH
Cleveland, OH
Columbia, SC
Columbus, OH
Dallas, TX
Dayton, OH
Daytona Beach, FL
Denver, CO
Des Moines, IA
Detroit, MI
Dutchess County, NY
El Paso, TX
Erie, PA
Flint, MI
Fort Myers-Cape Coral, FL
Fort Pierce-Port St. Lucie, FL
Fort Worth-Arlington, TX
Fresno, CA
Ft. Lauderdale, FL
Galveston, TX
Gary, IN
Grand Rapids, MI
Greensboro, NC
Greenville, SC
Hamilton, OH
Harrisburg-Carlisle, PA
Hartford, CT
Houston, TX
Indianapolis, IN
Jacksonville, FL
Jersey City, NJ
Kansas City, MO-KS
Knoxville, TN
Lakeland-Winter Haven, FL
Lancaster, PA
Lansing, MI
Las Vegas, NV-AZ
Little Rock, AR
Los Angeles, CA
Louisville, KY
Lubbock, TX
Madison, WI
McAllen-Edinburg-Mission, TX
Melbourne-Titusville-Palm Bay, FL
Memphis, TN
Miami, FL
Middlesex, NJ
Milwaukee, WI
Minneapolis-St. Paul, MN
Mobile, AL
Monmouth-Ocean, NJ
Myrtle Beach, SC
Naples, FL
Nashua, NH
Nashville, TN
Nassau-Suffolk, NY
New Haven-Meriden, CT
New London, CT
New York, NY
Newark, NJ
Newburgh, NY
Oakland, CA
Ocala, FL
Oklahoma City, OK
Omaha, NE
Orange County, CA
Orlando, FL
Pensacola, FL
Philadelphia, PA-NJ
Phoenix, AZ
Pittsburgh, PA
Portland, ME
Portland, OR
Providence-Fall River, RI-MA
Punta Gorda, FL
Raleigh, NC
Reading, PA
Riverside-San Bernardino, CA
Rochester, NY
Rockford, IL
Sacramento, CA
Saginaw, MI
Salinas, CA
Salt Lake City, UT
San Antonio, TX
San Diego, CA
San Francisco, CA
San Jose, CA
Sarasota-Bradenton, FL
Scranton--Wilkes-Barre--Hazleton, PA
Seattle, WA
Shreveport, LA
Spokane, WA
Springfield, MA
St. Louis, MO-IL
Stamford-Norwalk, CT
Stockton-Lodi, CA
Syracuse, NY
Tacoma, WA
Tampa-St. Petersburg-Clearwater, FL
Toledo, OH
Trenton, NJ
Tucson, AZ
Tulsa, OK
Utica-Rome, NY
Ventura County, CA
Virginia Beach, VA
Washington, DC-MD-VA
West Palm Beach-Boca Raton, FL
Wichita, KS
Wilmington, DE
Worcester, MA
York, PA
Youngstown-Warren, OH

Figure IV. 2. Odds ratios and 95% confidence intervals for admission to the hospital for renal/heat causes (graphs A and C) or respiratory causes (graphs B and D) among individuals aged 65 years and older during extreme heat on lag days 0-1 (graphs A and B) or over lag days 0-7 (graphs C and D) (1) vs. non-extreme heat among "reference individuals" (white females aged 65-78 years residing in the ZIP codes in the 25th percentile of percent non-green space, percent of residents without a high school degree, percent of residents who are nonwhite and percent of residents living below the poverty level), (2) for the added effect during extreme heat for males vs. females, nonwhites vs. whites, ages 79 or older vs. ages 65-78 or (3) for the added effect during extreme heat for interquartile range increases in percentages of non-green space, residents without a high school degree, residents who are nonwhite or residents living below the poverty level in a ZIP code in cities in the 25th and 75th percentiles of central AC prevalence (AC), May-September, 1992-2006.



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CHAPTER V

Dissertation Conclusion

The three studies comprising this dissertation have addressed several critical questions regarding the health effects of heat but have also raised additional questions. We have characterized the strength and direction of the association between hospital admissions and heat across the United States, over both short and longer-term time periods, and we have identified individual- and area-level characteristics of vulnerability to heat, particularly green space, in Michigan (as related to mortality) and in the United States (as related to emergency hospital admissions). However, the large amount of heterogeneity in the results points to future research needs.

In the United States as a whole, we have identified an association between hospital admissions for renal causes and respiratory causes and both moderate heat and extreme heat. For moderate heat, the effects were weak for respiratory admissions, but for both outcomes, the effects are of public health significance for extreme heat. Consistent with a review of studies worldwide, we found a null or protective association between cardiovascular admissions and heat (Turner et al. 2012). The contrasting pattern between heat and hospital admissions and heat and mortality with respect to cardiovascular disease suggests that heat effects may be more sudden in individuals with pre-existing cardiovascular disease, thereby prohibiting them from receiving life saving care in time, while the effects of heat on individuals with respiratory diseases may be more gradual. The strong association between heat and renal admissions suggests a need to target additional heat adaptation interventions towards individuals with pre-

existing renal conditions. However, it is not clear from our study design that all of the increase in renal admissions associated with heat is among individuals with pre-existing renal disease, and heat may in fact be precipitating new renal conditions in some patients.

The morbidity displacement pattern observed in the associations between heat and hospital admissions for cardiovascular and respiratory causes is strong compared to that quantified in heat-mortality studies. Hospital admissions may be more "malleable" than deaths in that individuals may have more personal control over the timing of the admission, and this may make daily hospital admissions rates more sensitive to daily temperature fluctuations. This pronounced displacement of events highlights the importance of accounting for displacement in calculating estimates of the long-term burden of heat-associated disease. This is often overlooked in that studies of the displacement effect often have not explicitly quantified it (e.g., Braga et al. 2001), or studies of the long-term burden of heat health effects use heat-health effect estimates based only on the immediate effects of heat (e.g., on lag days 0-3), without accounting for the subsequent decline in mortality rates (e.g., Peng et al. 2011). Characterizing the extent of morbidity or mortality displacement is not straightforward, though, and our own results were sensitive to the length of the time stratum in our case-crossover design—a problem analogous to the choice of degrees of freedom for the time spline in a time series study. Despite these challenges, we addressed this issue in our study of vulnerability to heat-associated hospital admissions, and we found increased vulnerability to heat over a longer lag period (0-7 days) as well as over the short-term. The effect of low education was even stronger over 0-7 days than 0-1 days, and this suggests that the pronounced morbidity displacement of heat-related admissions seen in the general population of individuals 65 and over may be lessened or absent in vulnerable subgroups.

Despite having only a course area-level measurement of green space (percent of green space within a ZIP code), we found green space to be significant modifier of both mortality (in Michigan) and hospital admissions in some cities. This is an encouraging finding given that green space is a highly modifiable characteristic—it is relatively easy, from a public health standpoint, to diminish the urban heat island effect through tree plantings, for example. Additionally, though air conditioning prevalence also modifies the association between heat and mortality or morbidity (confirmed in our study), urban heat island mitigation has the advantages as a public health intervention (over increasing air conditioning usage) of not contributing substantially to green house gas emissions through fossil fuel consumption and of not being susceptible to failures in electricity distribution.

The between-city heterogeneity in the modifying effects of various sociodemographic characteristics on the association between heat and mortality or morbidity may be due in part to the course resolution (ZIP code-level) of the area-level characteristics. The heterogeneity may also be due to the courseness of the measures themselves, .e.g, non-white, which served as a proxy for a wide variety of cultural characteristics, English language proficiencies and levels of community cohesion, and may have been reflecting entirely different underlying characteristics of heat vulnerability in different cities. Furthermore, sociodemographic characteristics can influence each other in complex, bidirectional ways not accounted for in our modeling. Though we deliberately avoided a principal component analysis or other variable reduction method prior to running our regression models, methods accounting for these complex interactions may help to elucidate underlying mechanisms in future research.

Consistent with recent studies of heat waves and mortality in the United States (Anderson and Bell 2011, Gasparrini and Armstrong 2011), we did not observe a strong added heat wave

effect in the association between heat and hospital admissions, above and beyond the independent effects of several days of intense, extreme heat. We used a novel method of estimating the added heat wave effect—as an interaction between independent days of extreme heat—to fully distinguish between the effect of duration and intensity. This finding suggests that heat health warning systems should not account strongly for the duration of heat as opposed to the intensity of the temperatures.

With extreme heat events expected to increase with climate change, the results of the three studies of this dissertation can inform climate adaptation efforts. These efforts include 1) identifying populations vulnerable to heat, especially through vulnerability mapping of individual- and area-level characteristics of vulnerability, and 2) understanding the importance of a morbidity outcome, emergency hospital admissions, in identifying thresholds for heat health warning systems, identifying vulnerable populations and estimating the present and future burden of heat on human health with respect to climate change.

However, more research is needed. These studies as well as previous studies of vulnerability have depended on the scant personal information in administrative databases (such as age, race and sex found in death records or hospital admissions) and U.S. Census information to characterize individual- and area-level vulnerability. The large amount of heterogeneity in the results of these studies suggests that the mechanisms underlying the associations observed in the main or modifying effects of sociodemographic characteristics on heat-associated mortality and morbidity have not been identified. Future research should use more detailed information on individual and neighborhood sociodemographic characteristics. Additionally, though high-powered in terms of their sample sizes, large administrative databases are usually not helpful in understanding the clinical or subclinical outcomes preceding the catastrophic outcomes of

emergency hospital admission or death. In turn, these precipitating events may be useful health outcomes in models identifying characteristics of vulnerability to heat.

In summary, we have addressed several critical issues in understanding heat-associated mortality and morbidity and characteristics of vulnerability to heat, but the large heterogeneity in results, particularly in characteristics of vulnerability to heat, suggest that more work is needed to identify the characteristics of subpopulations at risk from the heat health effects of climate change.

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APPENDIX A

Supplemental Information for Chapter III

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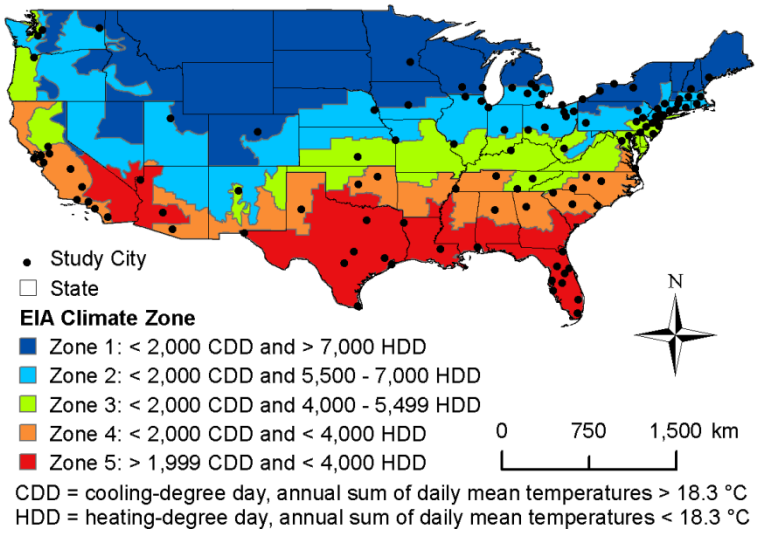
Figure A.1. Map of the 114 U.S. study cities and their corresponding Energy Information Administration (EIA) climate zones (Energy Information Administration 2010).



Akron, OH
Albuquerque, NM
Allentown-Bethlehem, PA
Atlanta, GA
Atlantic City, NJ
Austin, TX
Bakersfield, CA
Baltimore, MD
Bergen-Passaic, NJ
Birmingham, AL
Boston, MA
Baton Rouge, LA
Brownsville, TX
Buffalo, NY
Canton-Massillon, OH
Charleston, WV
Charlotte, NC
Chattanooga, TN
Chicago, IL
Cleveland, OH
Columbia, SC
Columbus, OH
Dallas, TX
Daytona Beach, FL
Dayton, OH
Denver, CO
Des Moines, IA
Detroit, MI
Dutchess County, NY
El Paso, TX
Erie, PA
Flint, MI
Fresno, CA
Galveston, TX
Gary, IN
Grand Rapids, MI
Greensboro, NC
Greenville, SC
Hartford, CT
Houston, TX
Indianapolis, IN
Jacksonville, FL
Jersey City, NJ
Kansas City, MO-KS
Knoxville, TN
Lakeland-Winter Haven, FL
Lansing, MI
Las Vegas, NV-AZ
Los Angeles, CA
Louisville, KY
Lubbock, TX
Madison, WI
Memphis, TN
Miami, FL
Middlesex, NJ
Milwaukee, WI
Minneapolis-St. Paul, MN
Mobile, AL
Monmouth-Ocean, NJ
Myrtle Beach, SC
Nashua, NH
Nashville, TN
Newark, NJ
Newburgh, NY
New Haven-Meriden, CT
New London, CT
New York, NY
Oakland, CA
Ocala, FL
Oklahoma City, OK
Omaha, NE
Orange County, CA
Orlando, FL
Philadelphia, PA-NJ
Phoenix, AZ
Pittsburgh, PA
Portland, ME
Portland, OR
Providence-Fall River, RI-MA
Raleigh, NC
Reading, PA
Rochester, NY
Rockford, IL
Sacramento, CA
Saginaw, MI
Salt Lake City, UT
San Antonio, TX
Sarasota-Bradenton, FL
Scranton--Wilkes-Barre--Hazleton, PA
San Diego, CA
Seattle, WA
San Francisco, CA
Shreveport, LA
San Jose, CA
Spokane, WA
Springfield, MA
Stamford-Norwalk, CT
St. Louis, MO-IL
Stockton-Lodi, CA
Syracuse, NY
Tacoma, WA
Tampa-St. Petersburg-Clearwater, FL
Toledo, OH
Trenton, NJ
Tucson, AZ
Tulsa, OK
Ventura County, CA
Virginia Beach, VA
Washington, DC-MD-VA
Wichita, KS
Wilmington, DE
Worcester, MA
West Palm Beach-Boca Raton, FL
Youngstown-Warren, OH

Figure A.2. Odds ratios (ORs) and 95% confidence intervals (CIs) for all cities for hospital admissions among U.S. elderly (May-September, 1992-2006) for lags 0-1 and the sum of lags 0-7 for 3 time stratum lengths of 5 real months (30-31 days per time stratum), 6 pseudo-months (25-26 days per time stratum) and 4 pseudo-months (38-39 days per time stratum) for (A) moderate heat (1 ºC increase in 2-day mean daily mean apparent temperature (AT) below the 95th percentile of 2-day mean AT), and (B) extreme heat (2-day mean AT above the 95th percentile).

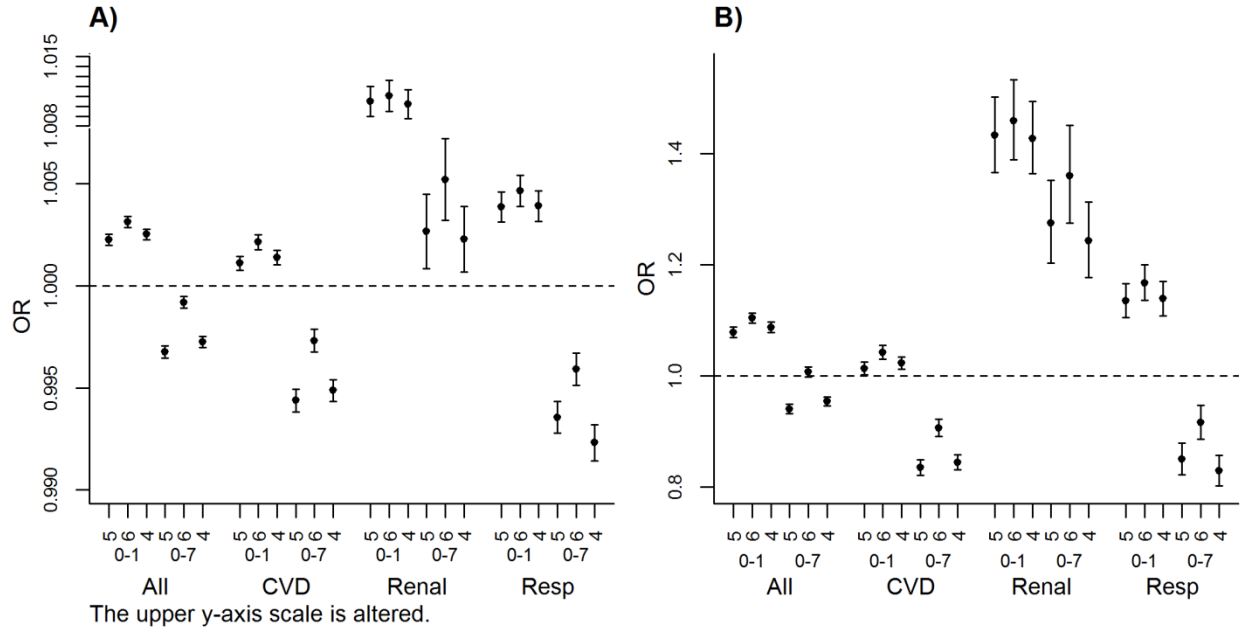
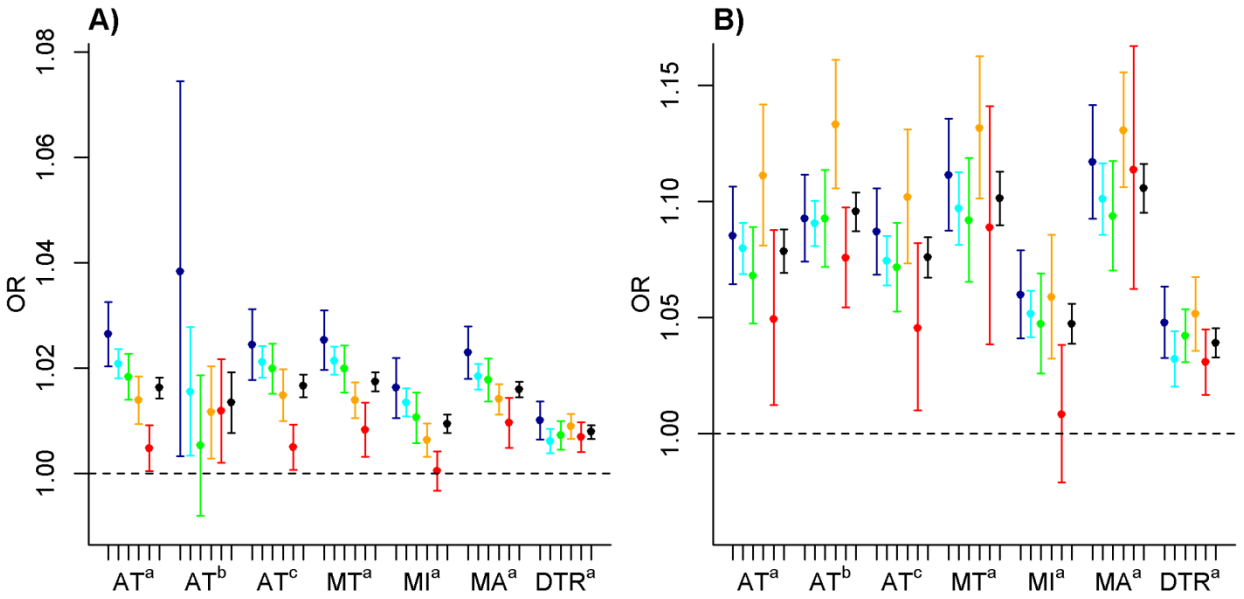


Figure A.3. Odds ratios (ORs) and 95% confidence intervals for hospital admission among U.S. elderly (1992-2006) for all natural causes for the mean over lag days 0-1 of different temperature metrics and thresholds for (A) an IQR increase (climate-zone specific) in moderate heat (e.g., $AT01_{MH}$) and (B) extreme heat, i.e., above the 90th or 95th percentile (e.g., $AT01_{EH}$).



[a] May-September cases, city-specific 95th percentile extreme heat threshold.
[b] April-October cases, city-specific cold, heat and 95th percentile extreme heat thresholds.
[c] May-September cases, city-specific 90th percentile extreme heat threshold.
For each metric, results in order from climate zones 1-5 (blue-red) and all zones combined (black).
IQR increase for all zones combined (deg. C): AT-7.2, MT-5.1, MI-5.3, MA-5.6, DTR-3.6.

Study Cities and Regions Methods

U.S. counties were ranked according to the number of hospital admissions due to cardiovascular disease from 2004-2006. Of the 200 counties with the most cardiovascular hospital admissions, 196 counties were within Metropolitan Statistical Areas (MSAs) in the continental U.S. and were assigned to their respective MSAs to form the “cities” in this study. The MSAs of Denver, CO, Portland, OR and Albuquerque, NM, though large, did not contain counties among the 200 counties with the highest number of cardiovascular hospital admissions, so the counties of Denver, CO, Jefferson, CO, Multnomah, OR, Clackamas, OR, Washington, OR and Bernalillo, NM were added. Cities were assigned to 5 climate regions using the U.S. Department of Energy, Energy Information Administration's climate zones (Energy Information Administration 2010), defined by numbers of cooling-degree days (CDDs, annual sum of daily mean temperatures above 18.3 °C) and heating-degree days (HDDs, annual sum of daily mean temperatures below 18.3 °C).

Alternative Model Including a Term for Cold Effects

Methods: In more complex models which incorporated all the months of the year in which heat waves occurred in our data set (April-October), we modeled AT as a double threshold piecewise linear spline (Armstrong 2006) to capture the possible U-shaped association, with increasing odds of hospital admissions above a heat threshold and below a cold threshold (since cool temperatures can occur in the April-October period). This spline included knots at the cold and heat thresholds and was constrained to have a slope of zero between the two thresholds. In these models, we also included the step function for AT above the city-specific 95th percentile of warm-season (May-September) as was included in the simpler models. We ran case-crossover models for each city for every combination of possible even-numbered integer AT heat and cold thresholds between the city-specific 10th and 90th percentiles of warm-season (May-September) AT, for each admissions cause where the hot threshold was forced always to be at least 18 °C. The heat and cold thresholds were constrained to occur at the same two points in each lag. We selected the model with the lowest Akaike's Information Criterion and also compared models with heat and cold thresholds to models without these thresholds using likelihood ratio tests.

Results: In the more complex models, the city-specific heat thresholds within each climate zone ranged widely, and the mean of the city-specific heat thresholds did not differ between climate zones with the exception of climate zone 5, which had a higher mean heat threshold (31 °C in climate zone 5 vs. 23, 26, 24 and 24 °C in climate zones 1-4, respectively for models of admissions for all causes). In likelihood ratio tests for each city, for admissions for all causes, the model was significantly improved by adding the cold and heat thresholds in only 44% of the cities as compared to a model with a single linear term below the 95th percentile of 2-day AT. For cardiovascular, renal and respiratory admissions, the models were improved by the addition

of cold and heat thresholds in only 29%, 20%, and 25% of the cities respectively. In Appendix A, Figure A.3, the moderate heat and extreme heat effects estimated by the more complex model were qualitatively similar to those estimated by the simpler model.

Alternative Threshold Identification Using SiZer

Methods: We also attempted to identify heat and cold thresholds at lags 0-1 and 2-3 using the SiZer method, which identifies significant increases or decreases in locally weighted polynomial smoothers for different spans of the smoother (Chaudhuri and Marron 1999). The motivation for doing this was to potentially provide a more objective way of identifying thresholds by exploring the full range of smoothing approaches (from very little smoothing to a great deal). For each city, we performed a time stratified case-crossover analysis using Poisson regression (Lu and Zeger 2006) of the association between daily hospital admissions counts and AT01 and AT23 as natural cubic splines with 3 df. The SiZer scatterplot was created from the AT values and partial residuals for each lag, and smoothers with differing bandwidths were fit to that scatterplot. For each city for each lag, we tested approximately 20-30 bandwidths (1 for each degree Celsius in the range of ATs for that city), and the bandwidths ranged from $\log_{10}(h) = 0$ to 2.

Results: The SiZer method did not allow us to identify clear heat and cold thresholds in many cities. Often, a smoother with a small span (a very "wiggly" smoother) had multiple significant increases and decreases in its slope and a smoother with a large span significantly increased (or decreased) over the full range of AT values at that particular 2-day lag, without any threshold. Furthermore, the point at which the function began to increase, decrease or flatten often depended entirely on the span chosen. This suggests that the threshold approach may not fit the data well, or may not be estimable. Consistent with this, a linear relation with temperature fit better than the threshold model in a majority of our cities.

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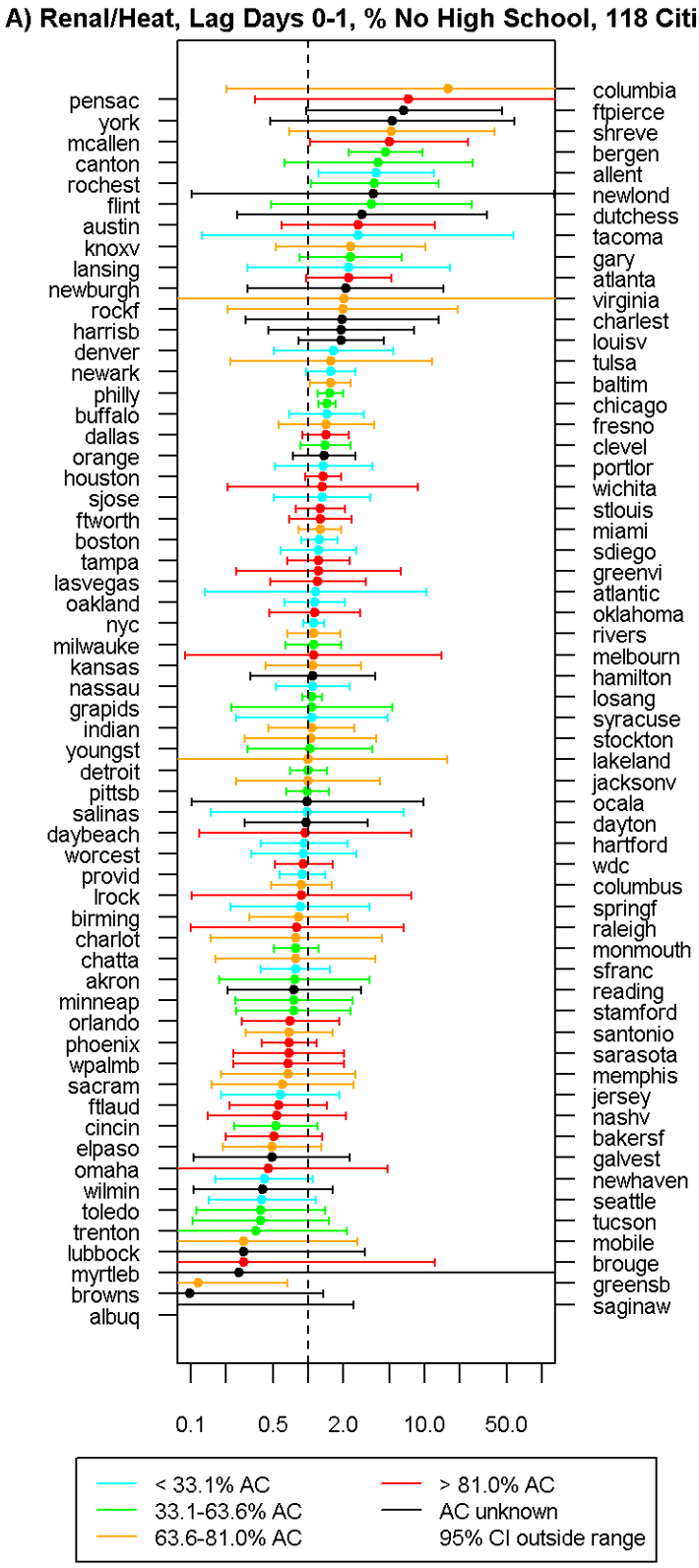
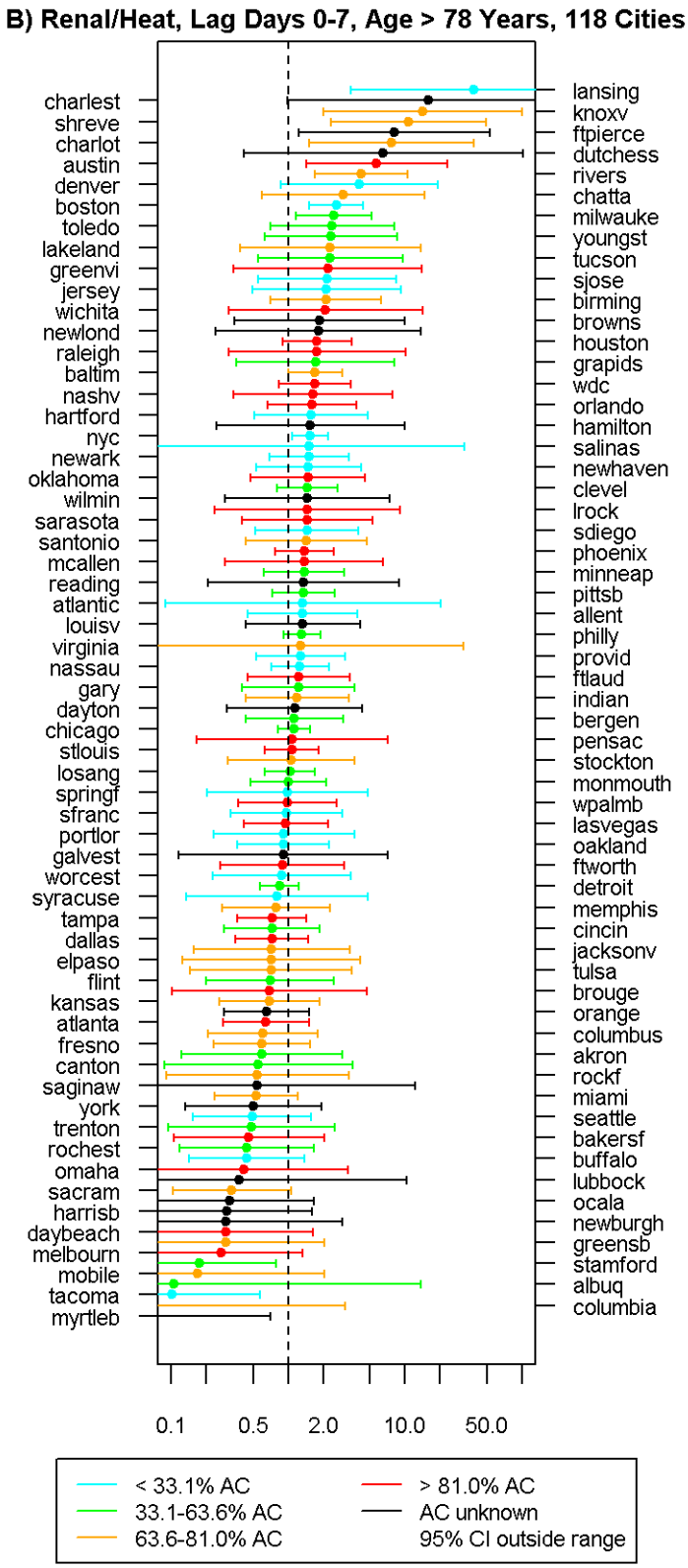
APPENDIX B

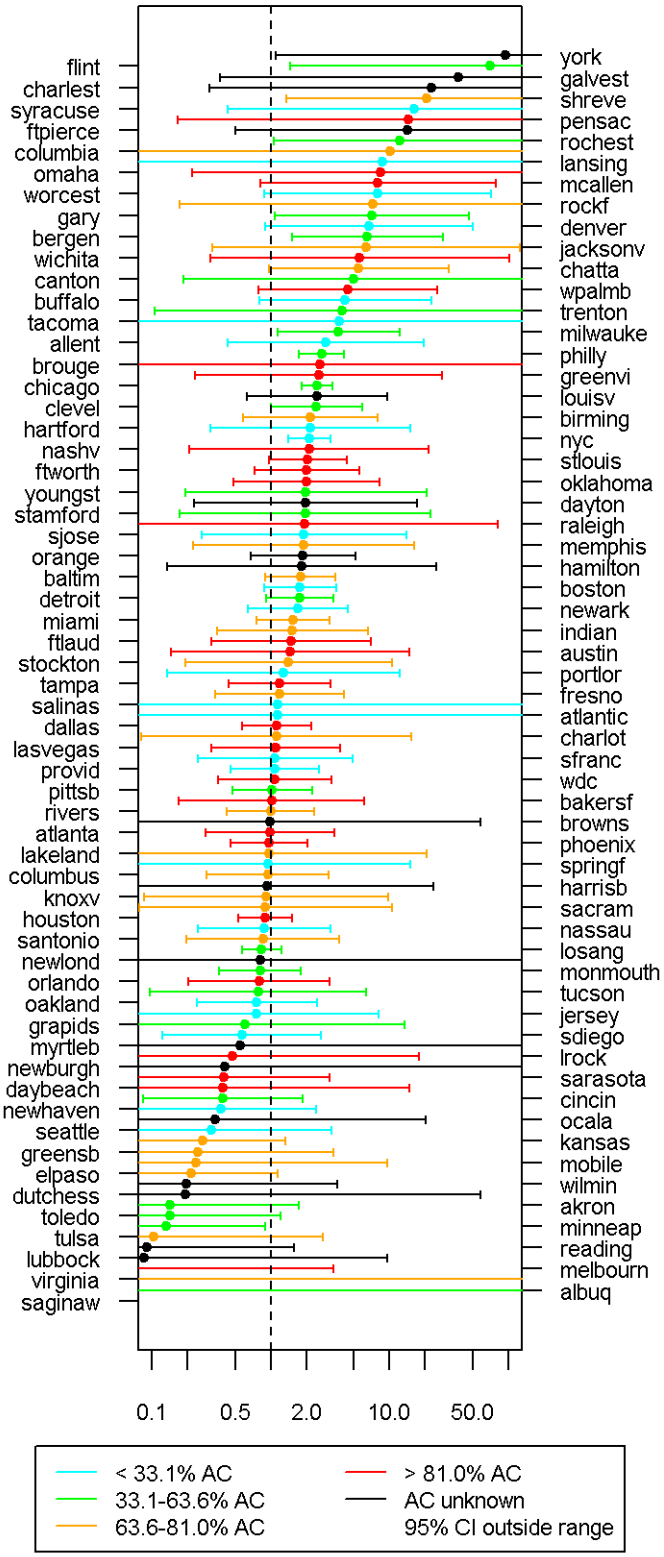
Supplemental Information for Chapter IV

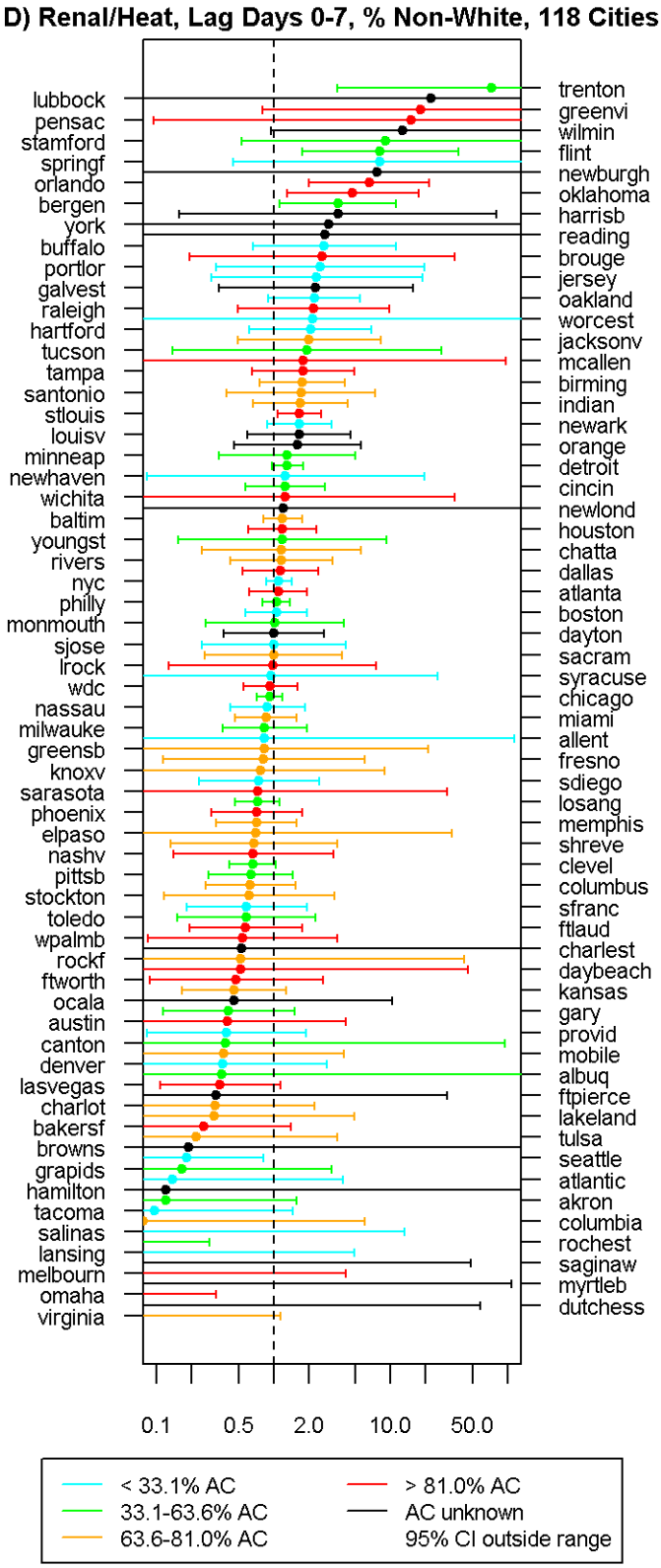
Figure B.1. Odds ratios (and 95% confidence intervals) for admission to the hospital among individuals aged 65 years and older, May-September, 1992-2006, during extreme heat for (A) renal/heat causes for the added effect during extreme heat on lag days 0-1 for an interquartile range increase in the percent of residents without a high school degree in a ZIP code, (B) renal/heat causes for the added effect during extreme heat over lag days 0-7 for individuals aged 79 years or older, (C) renal/heat causes for the added effect during extreme heat over lag days 0-7 for an interquartile range increase in the percent of residents without a high school degree in a ZIP code, (D) renal/heat causes for the added effect during extreme heat over lag days 0-7 for an interquartile range increase in the percent of residents of non-white race in a ZIP code, (E) renal/heat causes for the added effect during extreme heat over lag days 0-7 for an interquartile range increase in the percent of residents below the poverty level in a ZIP code, (F) respiratory causes for the added effect during extreme heat on lag days 0-1 for an interquartile range increase in the percent of residents of non-white race in a ZIP code.


A) Renal/Heat, Lag Days 0-1, % No High School, 118 Cities
pensac
york
mcallen
canton
rochest
flint
austin
knoxv
lansing
newburgh
rockf
harrisb
denver
newark
philly
buffalo
dallas
orange
houston
sjose
ftworth
boston
tampa
lasvegas
oakland
nyc
milwauke
kansas
nassau
grapids
indian
youngst
detroit
pittsb
salinas
daybeach
worcest
provid
lrock
birming
charlot
chatta
akron
minneap
orlando
phoenix
wpalmb
sacram
ftlaud
cincin
elpaso
omaha
wilmin
toledo
trenton
lubbock
myrtleb
browns
albuq
columbia
ftpierce
shreve
bergen
allent
newlond
dutchess
tacoma
gary
atlanta
virginia
charlest
louisv
tulsa
baltim
chicago
fresno
clevel
portlor
wichita
stlouis
miami
sdiego
greenvi
atlantic
oklahoma
rivers
melbourn
hamilton
losang
syracuse
stockton
lakeland
jacksonv
ocala
dayton
hartford
wdc
columbus
springf
raleigh
monmouth
sfranc
reading
stamford
santonio
sarasota
memphis
jersey
nashv
bakersf
galvest
newhaven
seattle
tucson
mobile
brouge
greensb
saginaw
0.1
0.5
2.0
10.0
50.0
< 33.1% AC
33.1-63.6% AC
63.6-81.0% AC
> 81.0% AC
AC unknown
95% CI outside range

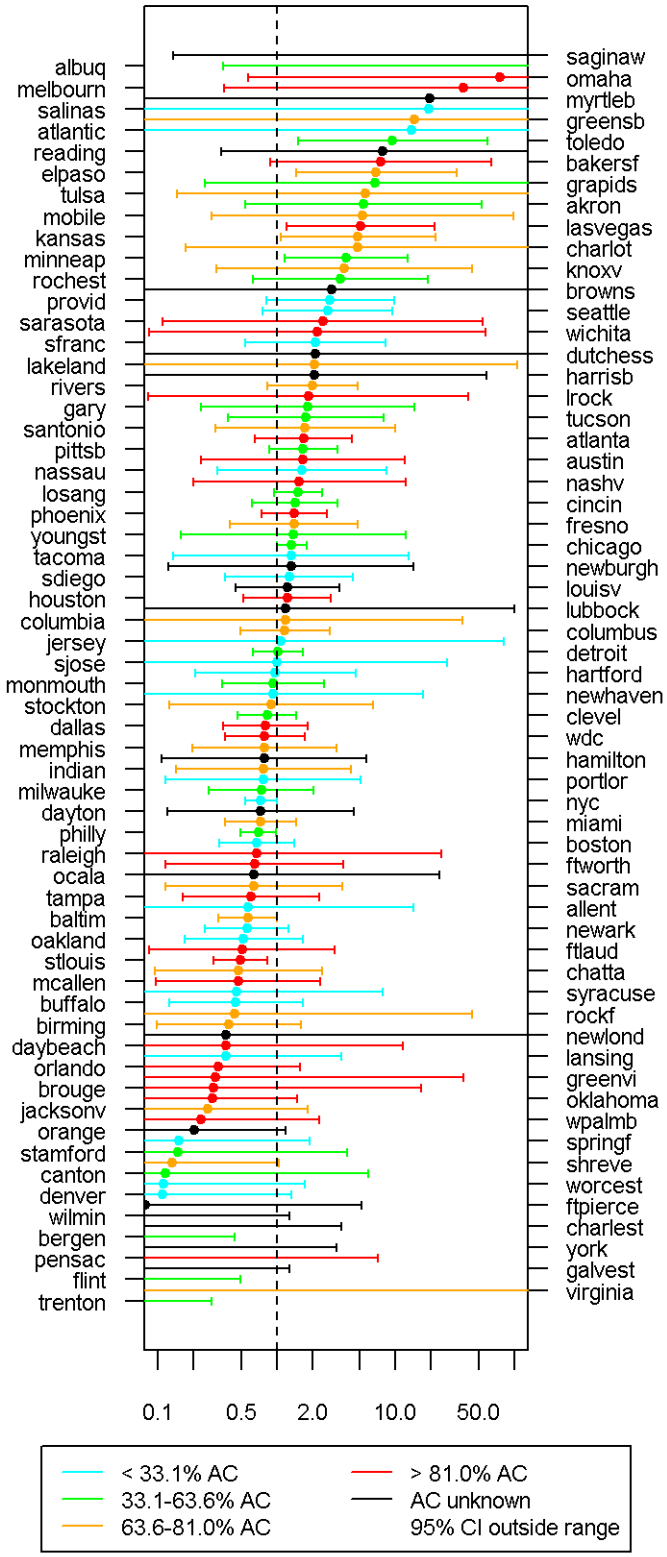

B) Renal/Heat, Lag Days 0-7, Age > 78 Years, 118 Cities
charlest
shreve
charlot
austin
denver
boston
toledo
lakeland
greenvi
jersey
wichita
newlond
raleigh
baltim
nashv
hartford
nyc
newark
oklahoma
wilmin
sarasota
santonio
mcallen
reading
atlantic
louisv
virginia
nassau
gary
dayton
chicago
stlouis
losang
springf
sfranc
portlor
galvest
worcest
syracuse
tampa
dallas
elpaso
flint
kansas
atlanta
fresno
canton
saginaw
york
trenton
rochest
omaha
sacram
harrisb
daybeach
melbourn
mobile
tacoma
myrtleb
lansing
knoxv
ftpierce
dutchess
rivers
chatta
milwauke
youngst
tucson
sjose
birming
browns
houston
grapids
wdc
orlando
hamilton
salinas
newhaven
clevel
lrock
sdiego
phoenix
minneap
pittsb
allent
philly
provid
ftlaud
indian
bergen
pensac
stockton
monmouth
wpalmb
lasvegas
oakland
ftworth
detroit
memphis
cincin
jacksonv
tulsa
brouge
orange
columbus
akron
rockf
miami
seattle
bakersf
buffalo
lubbock
ocala
newburgh
greensb
stamford
albuq
columbia
0.1
0.5
2.0
10.0
50.0
< 33.1% AC
33.1-63.6% AC
63.6-81.0% AC
> 81.0% AC
AC unknown
95% CI outside range

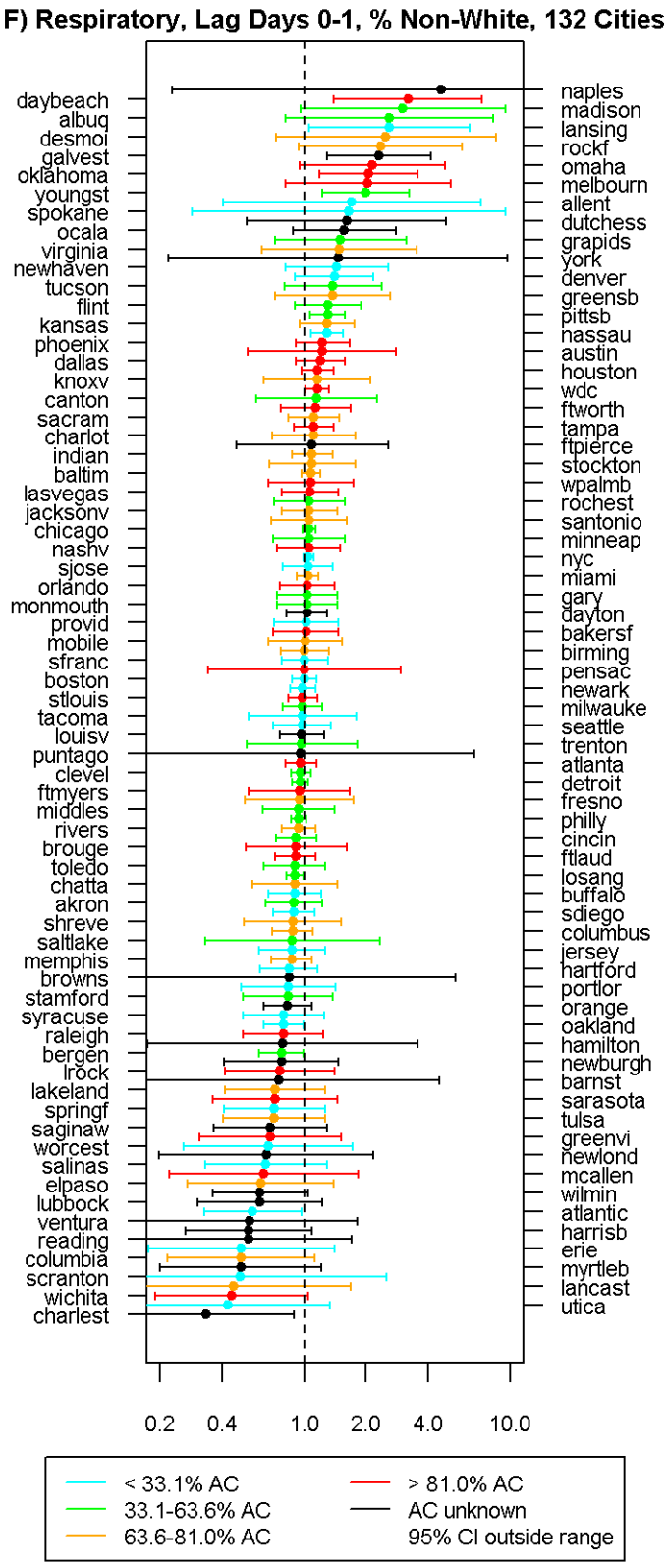
C) Renal/Heat, Lag Days 0-7, % No High School, 118 Cities




D) Renal/Heat, Lag Days 0-7, % Non-White, 118 Cities
lubbock
pensac
stamford
springf
orlando
bergen
york
buffalo
portlor
galvest
raleigh
hartford
tucson
tampa
santonio
stlouis
louisv
minneap
newhaven
wichita
baltim
youngst
rivers
nyc
philly
monmouth
sjose
lrock
wdc
nassau
milwauke
greensb
knoxv
sarasota
phoenix
elpaso
nashv
pittsb
stockton
toledo
wpalmb
rockf
ftworth
ocala
austin
canton
denver
lasvegas
charlot
bakersf
browns
grapids
hamilton
tacoma
salinas
lansing
melbourn
omaha
virginia
trenton
greenvi
wilmin
flint
newburgh
oklahoma
harrisb
reading
brouge
jersey
oakland
worcest
jacksonv
mcallen
birming
indian
newark
orange
detroit
cincin
newlond
houston
chatta
dallas
atlanta
boston
dayton
sacram
syracuse
chicago
miami
allent
fresno
sdiego
losang
memphis
shreve
clevel
columbus
sfranc
ftlaud
charlest
daybeach
kansas
gary
provid
mobile
albuq
ftpierce
lakeland
tulsa
seattle
atlantic
akron
columbia
rochest
saginaw
myrtleb
dutchess
0.1
0.5
2.0
10.0
50.0
< 33.1% AC
33.1-63.6% AC
63.6-81.0% AC
> 81.0% AC
AC unknown
95% CI outside range

E) Renal/Heat, Lag Days 0-7, % Below Poverty, 118 Cities




F) Respiratory, Lag Days 0-1, % Non-White, 132 Cities
daybeach
albuq
desmoi
galvest
oklahoma
youngst
spokane
ocala
virginia
newhaven
tucson
flint
kansas
phoenix
dallas
knoxv
canton
sacram
charlot
indian
baltim
lasvegas
jacksonv
chicago
nashv
sjose
orlando
monmouth
provid
mobile
sfranc
boston
stlouis
tacoma
louisv
puntago
clevel
ftmyers
middles
rivers
brouge
toledo
chatta
akron
shreve
saltlake
memphis
browns
stamford
syracuse
raleigh
bergen
lrock
lakeland
springf
saginaw
worcest
salinas
elpaso
lubbock
ventura
reading
columbia
scranton
wichita
charlest
naples
madison
lansing
rockf
omaha
melbourn
allent
dutchess
grapids
york
denver
greensb
pittsb
nassau
austin
houston
wdc
ftworth
tampa
ftpierce
stockton
wpalmb
rochest
santonio
minneap
nyc
miami
gary
dayton
bakersf
birming
pensac
newark
milwauke
seattle
trenton
atlanta
detroit
fresno
philly
cincin
ftlaud
losang
buffalo
sdiego
columbus
jersey
hartford
portlor
orange
oakland
hamilton
newburgh
barnst
sarasota
tulsa
greenvi
newlond
mcallen
wilmin
atlantic
harrisb
erie
myrtleb
lancast
utica
0.2
0.4
1.0
2.0
4.0
10.0
< 33.1% AC
33.1-63.6% AC
63.6-81.0% AC
> 81.0% AC
AC unknown
95% CI outside range