The Effects of Temperature and Use of Air Conditioning on Hospitalizations

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Abstract

Several investigators have documented the effect of temperature on mortality, although fewer have studied its impact on morbidity. In addition, little is known about the effectiveness of mitigation strategies such as use of air conditioners (AC). We investigated the association between temperatures and hospital admissions in California from 1999 to 2005. We also determined whether AC ownership and usage, assessed at the zip code level, mitigates this association. Because of the unique spatial pattern of income and climate in the state, confounding of AC effects by other local factors is less likely. We only included individuals who had a temperature monitor within 25 kilometers of their residential zip codes. Using a time-stratified case-crossover approach, we observed a significantly increased risk for hospitalization for multiple diseases including cardiovascular, ischemic heart disease, ischemic stroke, respiratory disease, pneumonia, dehydration, heat stroke, diabetes and acute renal failure with same-day apparent temperature. We also found that ownership and usage of air conditioning significantly reduced the effects of temperature on these health outcomes, after controlling for the potential confounding effects of family income and other socioeconomic factors. Our results demonstrate important effects of temperature on public health and the potential for mitigation.

Several investigators have documented the acute effect of temperature on mortality in the U.S. and Europe, and in developing nations (1-3). There are far fewer studies, however, on the effects of temperature on morbidity outcomes, such as hospitalizations (4-6). According to the recent IPCC report (7), temperatures are expected to increase in the future with more frequent and severe heat waves. Therefore, it is important to obtain a better understanding of these heat-associated health risks and susceptible populations for future surveillance and targeted interventions. In addition, relatively little is known about the effectiveness of proposed mitigation strategies, such as cooling shelters, and personal use of air conditioners (AC). Studies on the effects of actual AC use on temperature-related health outcomes, however, are limited, since data are typically available for AC prevalence, rather than AC use, and only for broad geographic regions. Thus, effects of AC may be confounded by other regional characteristics (8) such as demographic and economic factors. As a result, there is need for more localized estimates of the effects of temperature on morbidity and on the effectiveness of AC use in mitigating these effects.

For several reasons, California serves as an ideal study area for examining the effects of AC use on temperature-related adverse health. First, it includes a large and diverse population, residing within a wide array of climatic regions. Second, individual-level data at small levels of spatial scale over a majority of the state are available from surveys conducted by the California Public Utilities Commission (9). Finally, income is less likely to confound the estimates of the effects of AC. In general, incomes are higher in the coastal regions, but lower in the inland areas, such as the Central Valley. However, AC use is greater in the Central Valley where the summers are much hotter, and many homes in the coastal areas of California lack AC (9).

In this study, we used temperature data during the warm season in California to estimate the impact on several disease-specific categories of hospitalizations. To limit exposure misclassification, we limited our study to buffer areas with individuals living in zip codes within 25 kilometers (km) of a temperature monitor. Next, we quantified the likely reduction in health impacts based on both ownership and use of ACs using individual-level data for each buffer. Finally, we examined the potential confounding effect that local measures of family income may have on our effect estimates.

MATERIALS AND METHODS

Health outcome data

Data on disease-specific hospital admissions from 1999 through 2005 were obtained from the California Office of Statewide Health Planning and Development (OSHPD), Healthcare Quality and Analysis Division (10). We restricted our analysis to the warm season of May 1 through September 30, and abstracted information on date of admission and primary diagnosis, and patient's zip code of residence. Based on previous research (4, 5, 11), we considered the following conditions: several cardiovascular and respiratory diseases as well as diabetes, dehydration, heat stroke, intestinal infectious diseases, and acute renal failure. Using ArcGIS Version 9.2 (12), we used the population-weighted centroid to assign each zip code to the closest temperature monitor in the same climate zone, up to a maximum distance of 25 km. Information on climate zones came from the California Energy Commission (CEC), which divides California into 16 zones based on weather, temperature, energy use and other climatic factors. By requiring respondents assigned to a given monitor to be in the same climate zone, we attempted to reduce misclassification of temperature exposure. If more than one temperature monitor was within 25 km of the population centroid and was located in the same climate zone, residents of that zip code were assigned exposure from the closer monitor.

Weather data

Temperature data were obtained from two separate monitoring datasets: the California Irrigation Management Information System (CIMIS) (13) and the U.S. Environmental Protection Agency's Air Quality System (14). Mean, maximum, and minimum daily apparent temperature values in degrees Fahrenheit (°F) were calculated to account for temperature and relative humidity using a method that has been previously described (15).

Air conditioning and socioeconomic data

We obtained data on AC ownership and use from the 2004 California Residential Appliance Saturation Survey (RASS), a statewide utility survey sponsored by the CEC (9). From this survey conducted in 2003, we used approximately 21,900 responses from 1,272 zip codes statewide in 53 out of 58 counties. This mailed survey employed a stratified random sample design for all metered customers served by the participating utility companies. The stratification variables for the individually metered customers were electric utility, age of home, presence of electric heat, home type and climate zone. Survey questions obtained information about whether respondents had AC in their residences, with separate questions for central and room AC units. Additional questions were asked about their AC use during that year. Based on these responses, we calculated the separate prevalence of AC ownership and use for both central and room AC. Ultimately, responses were aggregated into six buffer-specific averages of AC prevalence and use including both prevalence and use of central AC only, room AC only and either central or room AC. For the 10% of respondents that indicated presence of AC but did not provide information on use, we assigned the buffer-specific rates of use obtained from the respondents with complete data.

To assess the relationship between AC and socioeconomic status, we used the 2003 RASS survey question concerning annual household income to create a buffer-specific average estimate for income. We also used zip code level data from the 2000 Census and created additional buffer-specific measures of median household income, population living in poverty, and population over 65 years of age. Buffer-specific estimates were determined by weighting zip code data by the associated population.

Similar to the spatial assignment of hospital data, each AC survey respondent was assigned to the closest temperature monitor within 25 km. Each buffer was required to have at least 25 respondents completing the RASS survey to be included in the analysis. Ultimately, there were 117 buffers with complete data.

Study design and data analysis

As in previous studies (11), we used a time-stratified case-crossover study design described by Levy et al (16) and Janes et al (17). In this method, temperature on the date of hospitalization (case) is compared to several control days (referent periods) occurring on the same day of the week within the same month and year. Since all referent periods are selected within the same month as the hospitalizations, seasonal or long-term effects are minimized. Besides examining the effect of same-day temperature (lag0), we also considered the effects of temperature on previous days: from 1 to 6 (lag1 to lag6), as well as several cumulative averages of temperature including same day and previous day (lag01), same day and the three previous days (lag03), and same day and the six previous days (lag06).

All analyses were conducted in two stages: first, we used the PHREG procedure in SAS statistical software (18) for conditional logistic regression, and obtained beta estimates for each buffer area. Then, we combined the buffer-specific beta estimates using a random effects meta-analysis (19), with the meta.summaries command in R statistical software's RMETA package (20). Meta-analyses were conducted for each of the climate zones and then for the entire state. Odds ratios (ORs) and 95% confidence intervals (CIs) were calculated for a 10 degree Fahrenheit (F) change in apparent temperature (daily mean, maximum, or minimum). The results are presented as the percent excess risk of hospital admission defined as: (OR - 1) x 100%.

To assess effect modification by AC, we performed a random-effects meta-regression in Stata version 8, using the revised METAREG package (21). In univariate analysis, the buffer-specific beta estimates were regressed on each of the buffer-specific AC prevalence and use metrics. In a second model, we included adjustment for buffer-specific income, as measured by the RASS survey.

Sensitivity analyses

We conducted several sensitivity analyses specifically for hospitalizations for respiratory and cardiovascular disease using different analysis parameters. First, to examine possible exposure misclassification associated with distance to the monitor, we reduced the inclusion radius to 10 km instead of 25 km. Second, to assess the effect of only assigning cases to monitors in the same climate zone, we conducted another analysis that allowed people to be assigned to a monitor in a different climate zone, provided their zip code was still within 25 km of the monitor. Third, to assess any possible bias created by excluding buffers lacking sufficient AC survey data, we reanalyzed the first-stage monitor-level analysis using all 209 temperature monitors and associated buffers in the state. Fourth, to determine whether the effects of air conditioning on the associations between hospitalization and cardiovascular and respiratory disease differed by age, we conducted separate analyses for those under age 65 years and 65 years or older.

RESULTS

The final data set included 117 buffers whose zip codes encompassed about 25.9 million people or about 87% of California's total population, as per the 2000 Census. Descriptive statistics on temperature, income and AC use and prevalence for the buffers in each climate zone are summarized in Table 1. Figure 1 shows the location of each climate zone. Table 1 also displays the climate zone-specific effect estimates relating temperature to hospitalization for respiratory and cardiovascular diseases. The results indicated several associations with temperature and larger effect estimates for the coastal versus inland climate zones (Climate Zone 1 was omitted due to the lack of data).

In Table 2 and Figure 2, the results of the meta-analysis are summarized for temperature and hospitalizations using cases that met our monitoring proximity criteria and residing in buffers with sufficient AC usage data. The number of cases of each disease is also displayed in Table 2. In general, the best model fit, according to t-statistics were observed for same-day (lag0) mean or maximum apparent temperature. For example, the effect of temperature was immediate for respiratory and cardiovascular disease

(Figure 3). Thus, all subsequent results shown are for lag0. Significant associations were observed between temperature and many of the cause-specific hospital admissions including hospitalization for total cardiovascular disease, ischemic heart disease and stroke, total respiratory disease, pneumonia, dehydration, heat stroke, diabetes and acute renal failure.

Table 3 summarizes the overall prevalence and use of the buffer-specific AC metrics and their impact on the association between temperature and hospital admissions. Overall, 64.9% of the survey respondents owned an AC and 60.1% used an AC during the year. Owning AC, using AC, owning central AC, and using central AC are highly correlated ($r > 0.97$). As a result, these measures have a very similar impact on the reduction of the temperature-hospitalization effect estimate. In addition, prevalence and use of "any" AC and of central AC were not significantly correlated with income ($r =\sim -0.1$). In contrast, ownership and use of room AC was negatively correlated with income ($r=-0.42$ and -0.43), indicating that the greater the family income, the less likely the presence of a room AC.

In our second stage of analysis, we regressed the first stage monitor-specific betas obtained from the temperature-hospitalization analysis on the various measures of AC prevalence. Table 3 displays the results for different AC prevalence and use on hospitalization for respiratory disease. For example, a 10% change in the proportion using a central AC relates to a difference of 0.5% in the excess risk associated with a temperature increase of 10°F (i.e., the effect is reduced from 2.6% to 2.1% per 10°F). The impact of owning or using any AC or central AC is very similar, given their high correlation, while owning or using only a room AC was not associated with any reduction in the temperature effect on respiratory admissions. The AC effect estimate did not vary when any of the socioeconomic covariates (income from the RASS survey, census-based median household income, % over age 65, and %

poverty in the census tract) were included in the meta-regression. Since the results were very similar, only data for the RASS survey income are presented in Table 3.

Table 4 summarizes the effect modification of AC prevalence on other outcomes. Owning and using AC, and owning and using central AC modified the effects of temperature for several of the disease categories examined, including pneumonia, all cardiovascular, IHD, ischemic stroke, dehydration, and heat stroke. Again, these measures were robust to additional adjustment by SES. Table 4 also displays the relative change in the first-stage beta coefficients relating to a 10% increase in AC prevalence. For example, for hospitalization for IHD, a 10% increase in prevalence is associated with a 0.6% difference in the temperature-associated effect, corresponding to a 36% reduction in the first-stage coefficient.

Our sensitivity analyses focused on cardiovascular and respiratory effects. The analysis using a 10 km buffer generated results similar to those using the 25 km buffer. However, when the monitor-level analysis is conducted without respect to climate zone by allowing individuals to be assigned to monitors in a different climate zone within 25 km, the effect of temperature on both outcomes was reduced, and for respiratory admissions, the AC effect modification is no longer statistically significant. Thus, there is some evidence that taking into account climatology and geography increased the precision of our estimates and the study power. We observed results similar to our original first-stage results when all 209 buffers in the state (including those buffers excluded from the original analysis due to lack of AC data) were examined. Finally, the effect of air conditioning differed by age for both outcomes. For cardiovascular disease a 10% increase in AC ownership resulted in an absolute reduction in excess risk of 0.76 (0.29, 1.22) for those 65 and older versus a reduction of 0.46 (-0.01, 0.92) in those under 65 years. For respiratory disease the absolute reduction in excess risk was 0.52 (0.05, 1.00) for those 65 and older versus a reduction of 0.33 (-0.20, 0.85) in those under 65 years.

DISCUSSION

Using data based on 117 buffer areas, we observed significant associations between increased apparent temperature and risk of hospitalization for several outcomes. The effects were observed using both daily average and maximum apparent temperature. Using buffer-specific data, we also observed significant reductions in temperature-related hospitalizations when central AC was present or used. Although we performed the meta regressions to determine the effect of AC on the temperature- hospitalization relationship, the meta regressions may serve to correct the biased estimates of exposure occurring when AC use was not taken into account. Therefore, the adjustment of effects by air conditioning use may have more to do with correcting exposure measurement error than effect modification. In addition, we found no evidence that income, or other measures of socioeconomic status, confounded the relation between temperature and hospitalization in California. Finally, our analysis indicated that hospital admissions were most strongly associated with unlagged temperature, a finding consistent with other temperature studies (22). For some outcomes, such as cardiovascular disease and respiratory disease, there is a suggestion of harvesting of the temperature effects because the effect estimates for lags 1 to 6 are null or negative. However, for other outcomes, such as dehydration, the effects remain significantly positive out to lag 3.

To our knowledge, this is one of the first studies that used localized measures of temperature exposure, AC prevalence and use, and family income. Rather than using MSA- or large county-based estimates of AC prevalence, we were able to assign AC prevalence using smaller spatial clusters. The use of more local data was likely to reduce measurement error, which was also reduced by keeping monitor assignments within similar climate zones. We found that in California, prevalence or use of central AC was not associated with income. This is likely a result of the positive gradient for temperature and AC prevalence from coastal to inland areas, but a mild negative gradient for family income. Specifically, based on our sample of 117 buffer areas in California, the correlation between central AC prevalence and family income was -0.04. In contrast, the correlation of these two variables, based on a national study using AHS survey data for 53 metropolitan areas was -0.32 (2). The inverse association in this national study likely represents broad regional differences in income, demographics and AC prevalence and would not account for income differences within these large metropolitan areas. In our study, income does not confound the observed negative association between central AC use and hospital admissions. Our finding that the prevalence of central AC, but not room AC, modified the heat-mortality association has also been reported in other studies that had access to both of these AC measures (23, 24). It is not clear whether room AC is ineffective in mitigating health effects or whether too few people in our study have room AC to observe effects.

Several investigators of ambient temperature and mortality have examined modification by AC prevalence (23-28). However, none of these previous investigations of mitigation of temperature impacts focused on morbidity outcomes, such as hospitalizations. Anderson and Bell (2) analyzed 107 U.S. metropolitan areas and reported associations between higher daily temperatures and all-cause and cardiovascular mortality. As in other studies, greater heat effects on mortality were observed in urban areas in the northeastern region of the U.S. Analyses of these data for effect modification indicated that greater heat impacts per °F were observed in metropolitan areas with higher income, unemployment, use of public transit and population density and with lower AC prevalence – all characteristics associated with the Northeast. As indicated by Vedal (8), a variable measured ecologically such as AC may be associated with several other regional factors, making it difficult to attribute effect modification to any single factor. Thus, the observed effect modification may be due to any or all of these factors, as well as unmeasured correlates. In addition, there is a greater likelihood of acclimatization in the warmer southern states where, over time, individuals may adapt and become physiologically more tolerant to high ambient temperatures.

Curriero et al. (26) found an association between hotter temperatures and mortality in a sample of 11 large U.S. metropolitan areas. Analysis for effect modification of this association using 2000 Census data indicated that stronger effects were observed in the North, in metropolitan areas with a higher percentage of the population not finishing high school or living in poverty, and with lower percentage of AC present in the homes, based on AHS data. In addition, the authors indicated that acclimatization to higher temperatures may play a role in consistently warmer regions. Clearly, separating out the effect of regional AC use versus socioeconomic (SES) factors in this 11-city study is challenging given the differences in other potential effect modifiers that vary by region. In addition, AHS data records AC prevalence but not use. While we observed very high correlations between AC prevalence and use in California, their relationship for the nation as a whole is less certain. Similar issues of confounding by regional characteristics may persist in other studies (25, 27)

While we cannot entirely rule out the possibility that our AC measures may be also correlated with other factors that modify the heat-hospitalization effect estimates, we have attempted to minimize this likelihood. First, our data showed no correlation across the buffer areas between family income and either central AC prevalence or use. It is likely that the correlation with other measures of SES is also low. Second, previous studies that have examined the impact of AC prevalence on the effects of either ambient temperature or outdoor air pollution have relied on census data on a large-scale level, such as county-wide average. We were able to examine effects within relatively small areas around each temperature monitor. Third, we utilized AC prevalence and use data collected at the local level to minimize measurement error related to both temperature and use of AC. Fourth, previous studies in California have indicated that the association between heat and adverse health is not confounded by common air pollutions, such as ozone and fine particles (4, 15). Nevertheless, we cannot rule out the possibility of some confounding of our AC metrics. In addition, the survey data for AC prevalence and use was for only one year and may have changed during the study years.

In summary, we observed significant associations between heat and several disease-specific hospital admissions in California. We have also observed that the use of central AC appears to significantly reduce the risk from higher temperatures. We caution, however, that increased prevalence of residential AC might not be an effective long-term strategy in regions where temperatures continue to increase. Power brown and blackouts have often occurred during periods of high heat stress. In addition, until substitutes for carbon-based fuels are widely instituted, energy demands associated with increases in residential ACs use will exacerbate the adverse impacts associated with fuel combustion. This includes the health and welfare effects of both air pollution and changes in the global climate.

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TABLE 1. Climate zone characteristics and hospitalization effect estimates per 10°F change in apparent temperature from meta-analysis of buffer areas, May through September, 1999 to 2005.

Zone	Reference city	Mean Apparent Temperature degrees Fahrenheit	AC ownership* (%)	AC use* (%)	Median annual income ($ from RASS)	Effect on respiratory admissions (% change per 10°F)	Effect on cardiovascular admissions (% change per10°F)
1	Arcata	NA	4.4	3.6	49,960	NA	NA
2	Santa Rosa	61.7	43.2	40.1	66,787	6.8 (2.8, 11.0)	3.1 (0.7, 5.5)
3	Oakland	58.6	10.5	9.0	72,216	2.9 (0.3, 5.6)	2.0 (0.2, 3.8)
4	Sunnyvale	62.6	48.4	43.0	79,354	2.7 (-0.7, 6.3)	1.9 (-0.3, 4.2)
5	Santa Maria	60.7	14.7	10.4	65,005	7.8 (-1.7, 18.1)	9.8 (3.6, 16.3)
6	Los Angeles	64.5	31.4	24.4	72,013	7.0 (2.1, 12.1)	5.1 (1.9, 8.4)
7	San Diego	67.7	31.7	23.2	65,992	6.3 (2.3, 10.5)	4.9 (2.2, 7.5)
8	El Toro	69.5	55.0	47.9	55,133	5.6 (3.2, 8.0)	4.0 (2.3, 5.8)
9	Pasadena	69.5	74.6	67.9	58,698	2.9 (1.6, 4.2)	0.7 (-0.2, 1.6)
10	Riverside	70.9	86.6	78.4	60,905	0.3 (-1.3, 1.9)	-0.3 (-1.4, 0.8)
11	Red Bluff	72.2	88.6	85.8	54,400	0.7 (-2.2, 3.7)	1.6 (-0.3, 3.6)
12	Sacramento	68.9	86.0	81.9	68,384	0.7 (-0.7, 2.1)	0.2 (-0.8, 1.1)
13	Fresno	74.2	88.7	85.9	49,049	2.1 (0.3, 4.0)	-0.3 (-1.5, 0.9)
14	China Lake	77.8	87.7	85.1	50,796	0.8 (-3.1, 4.8)	-0.4 (-3, 2.3)
15	El Centro	86.8	97.5	95.2	64,177	-1.2 (-4.3, 2.0)	-0.4 (-2.4, 1.7)
16	Mount Shasta	61.7	56.0	52.3	65,195	-4.1 (-14.4, 7.4)	3.0 (-4.4, 10.9)

*Includes both central and room air conditioners

TABLE 2. Percent increase in excess risk (95% confidence interval) per 10°F change in mean, maximum, and minimum same-day apparent temperature from meta-analysis of buffer areas.

	ICD9 code	Mean (%)	Maximum (%)	Minimum (%)	# Cases
Respiratory	450-519	2.6 (1.4, 3.7)	1.8 (1.2, 2.4)	0.6 (-0.6, 1.8)	473,104
Pneumonia	480-486	3.9 (2.4, 5.4)	2.7 (2.1, 3.4)	1.3 (-0.3, 2.9)	179,470
Asthma	493	0.9 (-1.5, 3.3)	1.2 (-0.2, 2.6)	-1.7 (-4.5, 1.2)	61,266
COPD	491-492	0.7 (-0.9, 2.4)	1.1 (0.1, 2.1)	-0.8 (-2.8, 1.3)	130,712
Cardiovascular	390-459	1.4 (0.5, 2.4)	1.0 (0.4, 1.5)	-0.8 (-1.7, 0.2)	1,014,444
Ischemic heart disease	410-414	1.7 (0.4, 2.9)	1.2 (0.6, 1.9)	-0.6 (-1.8, 0.7)	330,917
Stroke	430-438	1.6 (-0.01, 3.3)	1.2 (0.4, 2.1)	-1.5 (-3.0, -0.01)	184,267
Ischemic stroke	433-436	3.3 (1.6, 5.0)	2.2 (1.4, 3.1)	-0.6 (-2.1, 0.92)	145,752
Myocardial infarction	410	0.4 (-1.5, 2.4)	0.8 (-0.3, 1.9)	-3.0 (-5.0, -1.0)	118,816
Heart failure	428	-0.8 (-2.4, 0.7)	0.2 (-0.7, 1.1)	-2.6 (-4.3, -0.8)	161,012
Dehydration	276.5	11.2 (9.0, 13.6)	5.7 (4.4, 6.9)	6.2 (3.9, 8.6)	64,815
Heat stroke	992	364 (283, 462)	166 (135, 201)	153 (103, 216)	941
Diabetes	250	4.0 (1.9, 6.2)	1.8 (0.9, 2.8)	1.7 (-0.8, 4.2)	98,476
Acute renal failure	584	10.2 (7.2, 13.2)	4.9 (3.4, 6.4)	7.2 (3.3, 11.1)	34,878
Intestinal infections	001-009	2.6 (-0.5, 5.7)	1.2 (-0.6, 3.0)	1.3 (-2.4, 5.2)	22,258

TABLE 3. Reductions in respiratory hospitalizations per 10F change in apparent temperature by various air conditioner metrics.

AC Metric	Prevalence# (%)	Effect estimate, unadjusted* (95% CI)	Effect estimate, adjusted for income (95% CI)#
Owns central or room AC	64.9	0.51 (0.02, 1.0)	0.50 (0.01, 1.0)
Uses central or room AC	60.1	0.52 (0.03, 1.0)	0.51 (0.02, 1.0)
Owns central AC	54.6	0.53 (0.03, 1.0)	0.54 (0.04, 1.0)
Uses central AC	50.1	0.54 (0.04, 1.0)	0.55 (0.05, 1.1)
Owns only room AC	10.3	0.06 (-2.0, 1.9)	0.45 (-2.7, 1.7)
Uses only room AC	10.0	-0.10 (-1.9, 2.1)	0.26 (-2.6, 2.0)

Based on respondents in RASS survey.

* Absolute reduction in the risk of respiratory admissions per 10° F from a 10% increase in each AC metric. For example, a 10% increase in owning a central AC reduces the estimated respiratory effect of a 10° F change in temperature by 0.53.

TABLE 4. Effects of 10 percent increase in air conditioning ownership on the temperature-mortality relationship

Outcome	Absolute Reduction in Excess Risk *	Relative Reduction in Excess Risk* (%)
Respiratory	0.51 (0.02, 1.0)	19.9 (0.7, 39.1)
Pneumonia	0.76 (0.2, 1.3)	19.4 (5.3, 33.5)
COPD	0.1 (-0.6, .7)	4.2 (-56.6, 63.6)
Cardiovascular	0.71 (0.3, 1.1)	49.1 (19.9, 78.3)
Ischemic heart disease	0.60 (0.1, 1.1)	36.2 (4.6, 67.6)
Stroke	0.63 (-0.02, 1.3)	38.4 (-1.5, 78.1)
Ischemic stroke	0.67 (0.02, 1.3)	20.4 (0.6, 40.1)
Diabetes	0.04 (-0.8, 0.9)	1.0 (-20.1, 22.0)
Acute renal failure	0.21 (-0.9, 1.3)	2.1 (-8.4, 12.4)
Dehydration	1.29 (0.6, 2)	11.5 (4.9, 18.1)
Heat stroke	14.74 (7.0, 21.8)	4.0 (1.9, 6.0)

* Absolute signifies the effect the AC increase has on reducing the estimated percent change in mortality per 10° F while the relative signifies the percent reduction in the temperature-mortality coefficient due to the AC increase.
COPD= Chronic obstructive pulmonary disease

FIGURE LEGEND

Figure 1. Map of California with 16 climate zones.

Figure 2. Excess risk of mean apparent temperature on disease-specific hospital admissions for lag 0.

Figure 3. Excess risk of mean apparent temperature on cardiovascular and respiratory disease hospital admissions, by single lag day from 0 to 6.

FIGURE 1

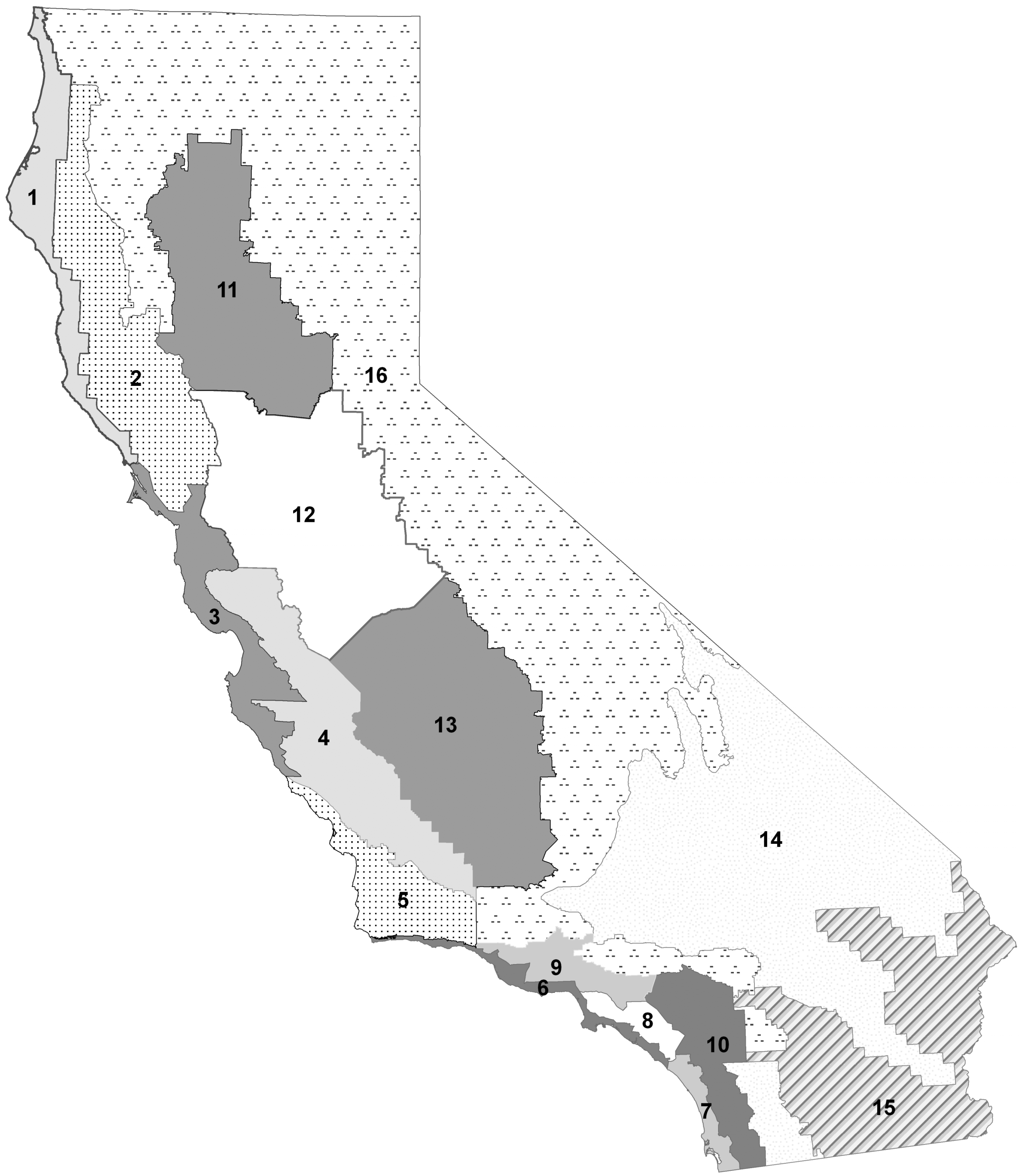
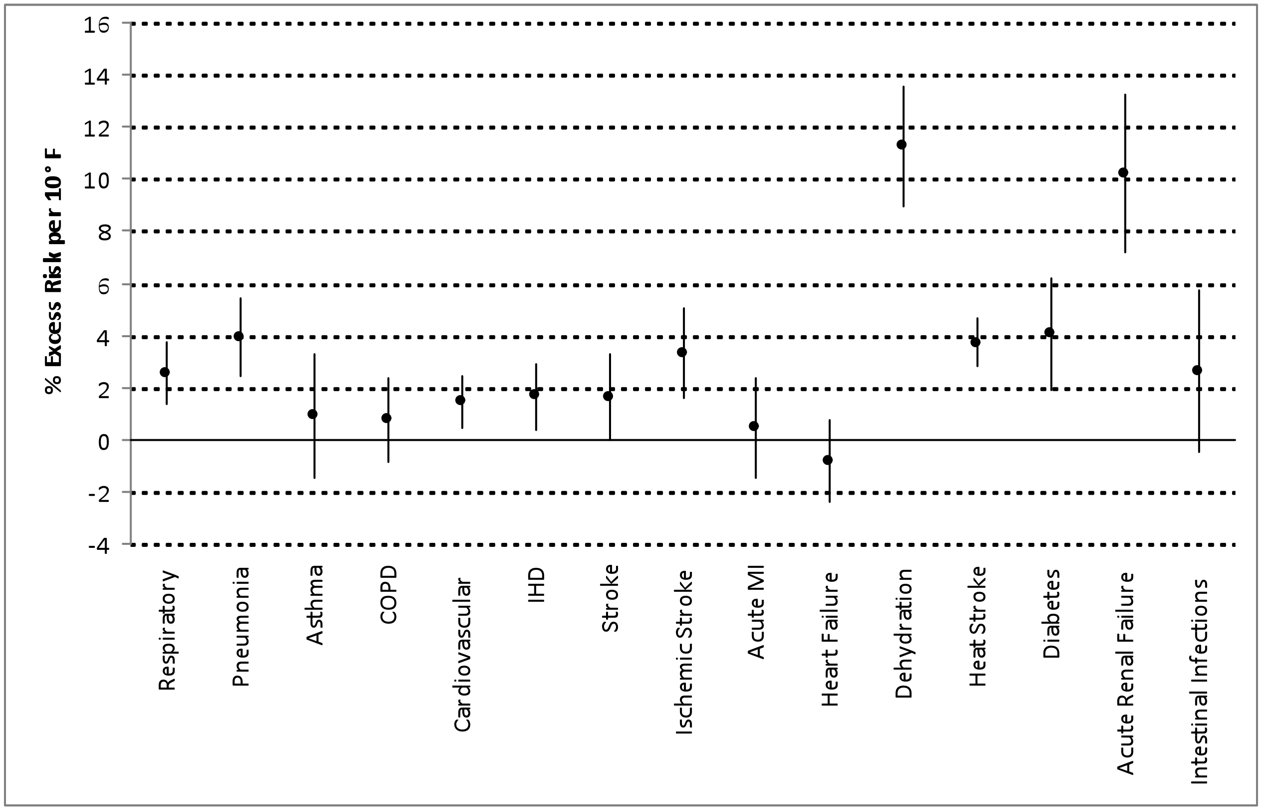


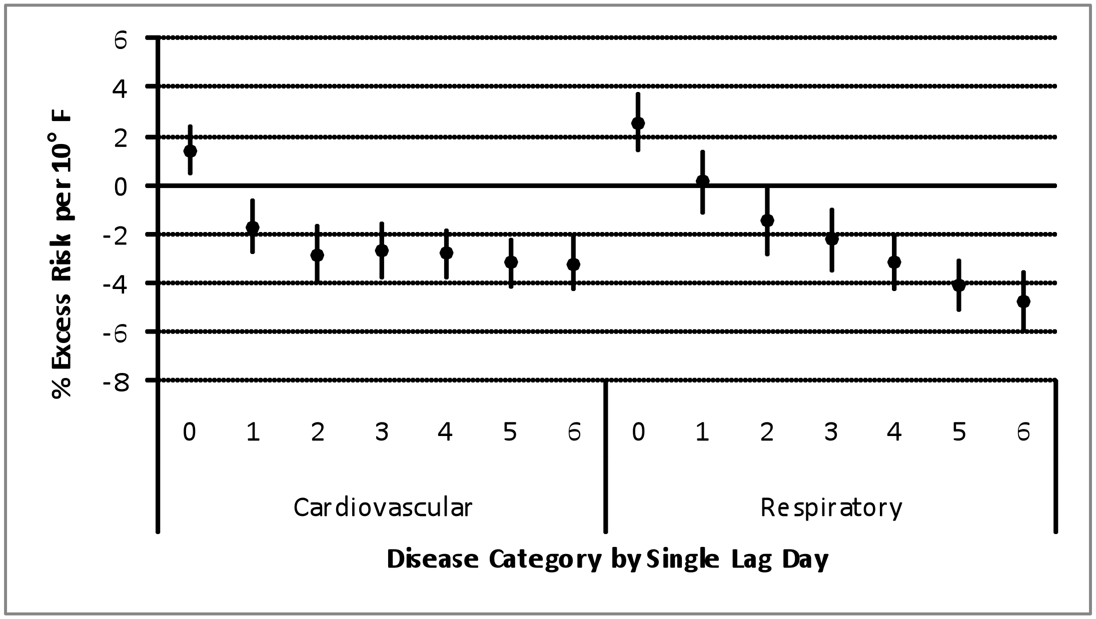
FIGURE 2.



Note: COPD = chronic obstructive pulmonary disease. IHD = ischemic heart disease.

Heat stroke has been scaled to excess risk/100.

Figure 3



6
4
2
0
-2
-4
-6
-8
% Excess Risk per 10° F
0 1 2 3 4 5 6
Cardiovascular
0 1 2 3 4 5 6
Respiratory
Disease Category by Single Lag Day

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