

**Impact of Extreme Heat on Emergency Medical Services  
in King County, WA**

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**Abstract**

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**Background:** Climate change is projected to have serious long-term consequences for public health. The existing body of literature has largely characterized increases in hospitalization and mortality in relation to extreme heat, but limited research exists characterizing the relationship between extreme heat and emergency medical services (EMS).

**Objective:** The primary objective of this research was to assess the impact of extreme heat on health and county resources through the use of high definition meteorological data and EMS call data for King County, WA.

**Methods:** Using EMS records and high-resolution meteorological data for 2007 through 2012, relative risk and time series analyses were conducted for the potential association between extreme heat and EMS calls. Extreme heat was defined as the 95<sup>th</sup> percentile of average daily county-wide maximum humidex values for Basic Life Support (BLS) EMS response data and the 99<sup>th</sup> percentile for Advanced Life Support (ALS) EMS response data. The analysis focused on health outcomes and level of transportation for all ages as well as six age categories and assessed for duration and cool down effects. Additional analyses of the impacts on cost were conducted.

**Results:** For all ages, all causes, there was an 8% increase in BLS calls on a 95<sup>th</sup> percentile heat day (29.7 °C) compared to a non-heat day and a 14% increase in ALS calls on a 99<sup>th</sup> percentile

heat day (36.7 °C) compared to a non heat day. The time series analyses demonstrated a 6.6% increase in BLS calls per degree increase above the statistically optimal threshold of 40.7 °C humidex and a 3.8% increase in ALS calls per degree increase above the optimal threshold of 39.7 °C humidex. Analysis by age category consistently identified significant results in 15-44 and 45-64 year olds, although 0-4 year olds and 65+ age groups also contained significant increases in risk for some health outcomes.

**Conclusions:** This research captured the volume of cases that may not be serious enough to warrant hospitalization, but still demand significant county resources, using EMS calls as a surrogate for adverse health outcomes. All-ages increases in risk and age-specific health effects were consistent with the limited existing research on EMS calls and heat, however the presence of increases in risk for relatively young populations was markedly different from regional effects demonstrated in more severe health metrics.

## Table of Contents

Abstract.....	3
Acknowledgements.....	10
Dedication.....	11
Background and Significance.....	12
Specific Aims.....	16
Methods.....	17
Data Sources.....	17
Exposure Analysis.....	20
Data Analyses.....	21
Relative Risk Analysis.....	21
Time-Series Analysis.....	23
Cost Analysis.....	24
Results.....	25
Relative Risk Analysis.....	25
Time-Series Analysis.....	30
Cost Analysis.....	34
Discussion.....	35
Limitations and Further Research.....	39
Conclusion.....	41
References.....	42

Appendix.....	47
1—Data Cleaning and Preparation.....	51
2—Data Cleaning and Preparation—R Code.....	67
3—Methods-Relative Risk Analysis.....	72
4—Methods-Relative Risk Analysis—R Code.....	76
5—Methods-Time Series Analysis.....	82
6—Methods-Time Series Analysis—R Code.....	85
7—Methods-Cost Analysis.....	98
8—Data Exploration.....	99
9—Results-Relative Risk Analysis.....	111
10—Results-Time Series Analysis.....	125
11—Results—Cost Analysis.....	131

## List of Tables

Table 1—Descriptive Statistics.....	19
Table 2—Relative risk results for BLS and ALS data by health outcome.....	26
Table 3—Relative risk results for BLS and ALS data by transportation type.....	28
Table 4—Time series results for BLS and ALS data by health outcome.....	32
Table 5—Time series results for BLS and ALS data by transportation.....	33
1.1—Descriptive statistics for demographic data.....	54
1.2—Descriptive statistics by gender, age, and age groups.....	54
1.3—Descriptive statistics for age distribution of EMS data and King County population.....	55
1.4—Descriptive statistics for location data.....	56
1.5—Descriptive statistics of the breakdown of property use and location type data.....	58
1.6—Descriptive statistics for medical treatment, outcome, and diagnosis information, not including procedures and flow chart data.....	59
1.7—Descriptive statistics of specific health outcomes-IDC.....	61
1.8—Descriptive statistics of specific health outcomes-Patient Type.....	63
1.9—Descriptive statistics for procedure codes.....	64
1.10—Descriptive statistics for flow chart data.....	65
1.11—Descriptive statistics of the breakdown of treatment data.....	66
4.1—Mean and max Humidex by summer month for study period.....	73
4.2—Humidex percentiles and model fit.....	74

9.1—RR for BLS and ALS for all cause, trauma, and non-trauma.....	113
9.2—RR for BLS data at 95 <sup>th</sup> percentile.....	114
9.3— RR for BLS data at 99 <sup>th</sup> percentile.....	115
9.4— RR for ALS data at 99 <sup>th</sup> percentile.....	117
9.5—RR for BLS and ALS for transportation.....	118
9.6—Call count for BLS and ALS transportation.....	119
9.7—Total call counts for BLS data at 95 <sup>th</sup> percentile.....	120
9.8—Total call counts for BLS data at 99 <sup>th</sup> percentile.....	121
9.9—Total call counts for ALS data at 99 <sup>th</sup> percentile.....	122
9.10—Average call counts for BLS and ALS data.....	123
9.11—Duration and cool down effects.....	124
9.12—Sensitivity Analysis.....	124
10.1—Time series analysis result for BLS data for health outcomes.....	128
10.2—Time series analysis results for ALS data for health outcomes.....	129
10.3—Time series analysis results for BLS and ALS data for transportation.....	130
11.1—Analysis of EMS call costs.....	131

## List of Figures

Figure 1—Combined trends plot.....	22
Figure 2—Cost analysis.....	35
8.1—Scatterplots of King County EMS calls per day by humidex.....	101
8.2—Scatterplot of King County EMS calls per day by humidex for BLS data with 2 knots....	102
8.3—Combined trend plots of call counts and humidex for entire study timeframe.....	103
8.4—Average maximum humidex for King County in 2009.....	104
8.5—Duration effects.....	105
8.6—Duration effects.....	106
8.7—Cool down effects.....	107
8.8—Cool down effects.....	108
8.9—Cool down effects.....	108
8.10—Fine tuning the model.....	109
8.11—Time Series analysis threshold selection.....	110
11.1— Difference in Average Daily Costs on a Heat Day Compared to a Non-Heat Day.....	132

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## **DEDICATION**

I would like to dedicate this thesis to my grandfathers,  
Hugh Calkins and Dr. Edward Radford,  
for their commitment to the pursuit of knowledge, involvement in promoting environmental and  
occupational health and justice, and inspiration for my academic endeavors.

## **BACKGROUND AND SIGNIFICANCE**

Climate change is projected to have serious consequences for public health through direct and indirect impacts of extreme weather events, changes to natural systems, and changes to human systems [IPCC 2014; Luber et al. 2014]. The growing body of climate change literature suggests that it is very likely that extreme heat will increase in frequency and duration in the coming years [IPCC 2013; Luber et al. 2014]. One of the more severe and measurable impacts of extreme heat on public health is an increase in mortality and morbidity, particularly in moderate climates and vulnerable populations [IPCC 2014; Luber et al. 2014]. According to the Centers for Disease Control and Prevention (CDC), exposure to excessive heat kills more people than any other weather-related phenomenon [CDC 2010]. As characterization of this relationship has developed, focus has shifted from the extremely severe, comprehensive mortality health outcome to more specific and potentially less severe health outcomes including mental illness [Hansen et al. 2008], preterm births [Carolan-Olah et al. 2014; Strand et al. 2011; Wang et al. 2013], and health events treated by emergency medical response (EMS) services [Brunetti et al. 2014; Dolney et al. 2006; Kue et al. 2013; Ng et al. 2014; Turner et al. 2013].

### **Existing Research On Extreme Heat And Health**

It is well established that there is a positive association between extreme heat and adverse health outcomes, including mortality [Busch Isaksen et al. 2014<sup>2</sup>; Curriero et al. 2002; Golden et al. 2008; Medina-Ramon et al. 2006; Vaidyanathan 2013] and morbidity [Busch Isaksen et al. 2014<sup>1</sup>; Knowlton et al. 2008; Mastrangelo et al. 2007], with cardiovascular, respiratory, and heat illness often cited as the cause of death or hospitalization. According to the CDC, heat exposure is known to cause heat rashes and heat strokes, as well as aggravate chronic diseases

(primarily those related to the cardiovascular and respiratory systems) and increased rates of death [CDC 2010].

Recent research at the University of Washington characterized the association between local extreme heat and health by combining high-resolution meteorological data for King County, WA from 1980-2010 with local hospitalization and mortality records.

One study demonstrated that the "all-ages relative risk of mortality on a heat day (above the 99<sup>th</sup> percentile) was 10% greater than on a non-heat day, with risk increasing 2.12% for each degree increase in humidex above 36.0 °C." [Busch Isaksen et al. 2014<sup>2</sup>]. A second study found that "the all-ages relative risk of hospitalization on a heat day (above the 99<sup>th</sup> percentile) was 2% (non-significant) greater than on a non-heat day, with risk increasing 1.59% for each degree increase in humidex above 37.4 °C" [Busch Isaksen et al. 2014<sup>1</sup>]. Building on this research, the current study assessed the association between extreme heat and emergency medical service (EMS) calls, using calls as a health metric that captures a higher volume of generally less severe cases.

Existing literature focusing specifically on EMS call volumes and extreme heat is relatively limited. To the author's knowledge, fifteen studies currently exist examining this association with varying definitions of extreme heat as well as varying approaches to quantifying EMS calls. Of these studies, six are from North America, five are from Australia, three are from Europe, and one is from Japan, yet all studies found significantly increased call volumes associated with extreme heat. Heat is more commonly described in these studies using temperature alone rather than a measure of apparent temperature, such as humidex, that includes relative humidity. Additionally, the analyses varied in their approach to defining extreme heat, with some using a specified number of consecutive days above a threshold and others

constructing time series analyses of temperature with fluctuating cutoffs. Some of the studies focusing on all causes of calls also included age grouping and cardiac, respiratory, and non-trauma health outcomes. Increases in risk ranged from 9% to 16% when comparing heat days or events to a reference heat measure [Cerutti et al. 2005; Dolney et al. 2006; Kue et al. 2013; Nitschke et al. 2011; Schaffer et al. 2012], while increases in risk resulting from time series analyses ranged from 1.45% [Alessandrini et al. 2011] to 29% [Bassil et al. 2010] per degree increase in heat. Kue et al. (2013) was the only study to specifically include EMS transportation as a variable of interest within the analysis.

Studies focusing on specific health outcomes rather than all causes of calls found increases in heat-related dispatch (HRD) [Golden et al. 2008; Hartz et al. 2012; Hartz et a. 2013], pre-hospital electrocardiograms (ECG) [Brunetti et al. 2012], and heatstroke [Ng et al. 2014]. In an EMS related meta-analysis, Hess et al. (2009) identified additional extreme heat-related factors such as hazards resulting from multi-system failures (e.g., power-outages) with the potential to increase demand on emergency medicine.

### **Vulnerability In Heat Illness**

The Pacific Northwest is an especially vulnerable area of the United States in regard to the effects of extreme heat on health. Curriero et al.'s 2002 research into the relationship between temperature and mortality demonstrated a stronger association in northern cities in the U.S., with a relatively greater risk of mortality at lower temperatures when compared to southern cities. Additionally, Reid et al. (2009) reported that the Pacific Coast has a relatively greater vulnerability to extreme heat than most other areas of the U.S.; the top factors contributing to the variance in this vulnerability were social/environmental vulnerability (e.g. poverty), social

isolation, low air conditioning prevalence, and the proportion of the population that is elderly or has diabetes. On an individual level, personal characteristics including age, physical fitness, and general health have been shown to impact an individual's vulnerability to heat by affecting thermoregulation of body temperature [Buresh et al. 2005; McKinnon et al. 2005; Naughton 2002; Naughton et al. 2008].

### **Emergency Medical System (EMS)**

The EMS of King County is a two-tiered system comprising basic life support (BLS) provided by emergency medical technician-trained firefighters who are authorized to provide non-invasive care, and advanced life support (ALS) provided by paramedics who are authorized to provide more advanced patient care, including intubation, manual defibrillation, and intravenous medications. When a call is placed to local 911 call centers, the dispatcher determines the level of care needed based on information provided by the caller. BLS responders are sent to all medical calls and ALS responders are sent when deemed necessary. In the period spanning 2007 -2012, there were approximately 30 agencies covering 165,000 BLS responses per year and six agencies covering 45,000 ALS responses per year [PHSKC 2012].

### **EMS Financial Costs**

In 2011, ALS services received approximately 62% of EMS funds for 20% of the calls while BLS received approximately 26% of funds for 80% of the calls (the remaining 12% of funds went towards administrative and program costs) [PHKSC 2012]. This demonstrates a significant difference in the financial burden on the county from an ALS level of response compared to BLS. There are a number of factors that contribute to this difference in cost, but

regardless of an individual's needs, all costs associated with EMS responses are free of charge to the patient, including transportation when needed. The funding for these services comes almost exclusively from property taxes. Since county fund forecasts predict a trend of increasing expenditures with decreasing revenue, and with expenditures already exceeding revenue (PHKSC 2014), a dramatic increase in calls or change in the nature of calls due to patterns in extreme weather conditions may have a significant impact on county financial planning in addition to the increased demand on physical EMS resources in the form of vehicles, personnel, or medical equipment.

### **SPECIFIC AIMS**

The objective of this research was to characterize the relationship between extreme heat and emergency medical service (EMS) calls in King County, WA. The overarching hypothesis of the study posits that when extreme heat occurs, there will be an associated positive increase in EMS calls. Given that the expected increase in EMS calls would be primarily due to the increase in heat, the study also focused on assessing potential differences in the reasons for the calls (specific health outcomes) as well as the level of care required (basic life support vs. advanced life support) and results of the calls (treat-on-site vs. transport). Additional questions of interest included the influence of age, gender, and location type on the composition of the calls. Using King County EMS records and high-resolution meteorological data, this research captured the volume of cases that included those not serious enough to warrant hospitalization, but still demanded significant county resources.

## METHODS

All methods used Oracle's MySQL Workbench 5.2.47 CE [Oracle MySQL Workbench 2013] for data storage and RStudio version 0.97.449 for data analysis [RStudio 2012].

### EMS Data Preparation

King County Emergency Medical Services Division of Public Health provided the emergency medical service (EMS) data with the approval of the University of Washington's Human Subjects Division. The data included all calls during the warmer five-month period, May 1<sup>st</sup> through September 30<sup>th</sup>, for the six-year study timeframe, 2007 through 2012. The EMS data consisted of two datasets—one for basic life support (BLS) and the other for advanced life support (ALS). Since all calls within King County, WA receive a BLS response regardless of whether or not an ALS unit responds, BLS was the primary dataset for this analysis. Initial data management conducted by EMS personnel involved compiling all EMS calls during the study timeframe, merging duplicate patient entries, and deidentifying individuals. Once this was completed, the datasets were delivered to UW researchers for additional preparation and analysis. EMS variables integrated into this analysis included those relating to the date and location of call, age and gender of the patient, primary health concern, transportation needs of the patient, and level of care provided by EMS. Information regarding race/ethnicity and socioeconomic status were not available for this dataset.

Health outcomes used for this study were based on the main reason the patient required emergency medical services as determined by the EMS responder, termed patient type code. These determinations were based on the patient's signs and symptoms, but are not identical to the International Classification of Disease (ICD) codes used in hospital settings. The three

broadest categories of health outcomes (all causes, trauma, and non-trauma) capture the overall impacts of extreme heat on emergency medical services. In addition to those broad categories, this analysis incorporated all non-trauma call classifications to better analyze the impacts of extreme heat on specific health outcomes. These classifications are listed in Table 1. Additional specific health outcomes were selected *a priori* based on available patient type codes and recent research [Busch Isaksen et al. 2014<sup>1,2</sup>] for their potential relationship to extreme heat (Table 1)

The level of transportation category contained four responses: no transportation, BLS transportation, ALS transportation, and other transportation. BLS and ALS transportation responses indicated that the EMS response team transported the patient to a medical facility. It should be noted that BLS transportation may appear in the ALS dataset and vice versa since both BLS and ALS teams may respond to the same call, but only one unit is necessary for transport. Other transportation primarily includes private ambulance services, but also includes any other form of transportation to a medical facility from the site of the EMS call.

Prior to analysis, the EMS data required preparation in the form of eliminating calls with missing age and/or gender, collapsing specific variable codes into higher classifications, and grouping ages into six categories. Calls missing age and/or gender data were excluded from this study for two reasons. First, recent research demonstrated effect modification of the association between extreme heat and health [Busch Isaksen et al. 2014<sup>1,2</sup>; Nitschke et al. 2011]. Second, calls missing age and gender data also were commonly missing data in other fields. Since age imputation introduces uncertainty and variables of interest to the study tended to be missing in these calls, the data was eliminated from the analysis. The exclusion of this data reduced total call counts from 441,119 to 361,434 in the BLS data and 121,974 to 94,565 in the ALS data.

Table 1: Descriptive statistics for gender, age, age groups, patient type, and level of transportation, for both BLS and ALS final analysis datasets. Statistics include number of observations (n) and percent of total data (% total).

		n(% of total)	
		BLS	ALS
Gender		361434	94565
	Male	174667 (48)	48779 (52)
	Female	186767 (52)	45786 (48)
Age		361434	94565
	0-4	10436 (3)	2141 (2)
	5-14	11414 (3)	1654 (2)
	15-44	116587 (32)	23194 (25)
	45-64	9887 (27)	30426 (32)
	65-84	80221 (22)	25407 (27)
	85+	43899 (12)	11743 (12)
Patient Type		309385	90579
Non-Trauma		238045 (77)	82232 (91)
	Abdominal/Genito-Urinary	26452 (9)	5172 (6)
	Alcohol/Drugs	17353 (6)	4253 (5)
	Anaphylaxis/Allergic Reaction	3515 (1)	1145 (1)
	Cardiovascular	30259 (10)	24130 (27)
	Metabolic/Endocrine	9439 (3)	4286 (5)
	Diabetes	7075 (2)	3841 (4)
	Neurological	47986 (16)	13551 (15)
	Suspected CVA	6432(2)	1354 (1)
	Suspected TIA	694(0)	68 (0)
	Seizures	10956 (4)	3827 (4)
	Febrile Seizures	1037 (0)	289 (3)
	OBGYN	2854 (1)	992 (1)
	Other Medical	58164 (19)	14324 (16)
	Heat Illness & Dehydration	3400 (1)	514 (1)
	Psychological	18149 (6)	3267 (4)
	Respiratory	23874 (8)	11112 (12)
	Asthma	1130 (0)	583 (1)
	Emphysema/COPD	812 (0)	580 (1)
Trauma		47005 (15)	6127 (7)
Other-Non Diagnostic		24335 (8)	2220 (2)
Level of Transportation		354526	93608
	No Transportation	87174 (25)	12016 (13)
	BLS Transportation	203679 (57)	36444 (39)
	ALS Transportation	41919 (12)	42744 (46)
	Other Transportation	21754 (6)	2404 (2)

The patient type variable contained a unique code for each individual medical concern that required collapsing into higher, more general categories. These categories were specified within the EMS data dictionary [PHSKC, 2010]. The six age categories used for the analyses

were created to refine characterization of the potential effects of heat on health within the population. Ages were grouped into categories based on previously used cutoffs [Busch Isaksen et al. 2014<sup>1,2</sup>] of 0-4, 5-14, 15-44, 45-64, 65-84, and 85+. See table 1 for descriptive statistics and appendices 1 and 2 for more detail.

## **Population Data**

Background population data was sourced from Washington State's Office of Financial Management [OFM 2012; OFM 2013] This data was available for all six years of interest and was grouped in five-year age increments. As a result, it required collapsing into the age groups of interest for this study.

## **Exposure Assessment**

Meteorological data was produced by the University of Washington's Climate Impacts Group based on the Parameter-elevation Relationships of Independent Slopes Model (PRISM) [Maurer et al. 2002]. This model was developed at Oregon State University and generated data on a ~1/16<sup>th</sup> resolution (4 km x 7.5 km) grid using climate data from the National Oceanic and Atmospheric Administration's Global Historical Climate Network-Daily (GHCN) database [NOAA 2009]. Daily temperature (min/max), humidity, and precipitation were available for each grid cell, but only temperature and humidity were necessary to calculate average countywide maximum humidex values (°C); humidex values provide the apparent, or felt temperature [Canadian Centre for Occupational Health and Safety 2011]. To calculate this heat metric daily maximum temperatures and relative humidity were first estimated for the center of each grid cell and then averaged across the county using the humidex equation below.

$$f(T, H) = T + (5/9) \times (v - 10), \quad v = (6.112 \times 10^{(7.5T/237.7+T)}) \times H/100,$$

Where T is the air temperature (°C), H is the humidity (%) and v is the vapor pressure. Trends in humidex values compared to total call counts by day is illustrated in Figure 1.

## Data Analysis

### RELATIVE RISK

The relative risk (RR) approach used Poisson regression to estimate the difference in expected EMS counts on heat days compared to non-heat days after accounting for variation within the population, thus allowing for comparison across different years. The analysis was conducted for both the BLS and ALS datasets for all causes, trauma, non-trauma, all patient type groups, as well as specific patient types identified earlier and level of transportation by all ages as well as for the 6 age categories. The RR equation is as follows:

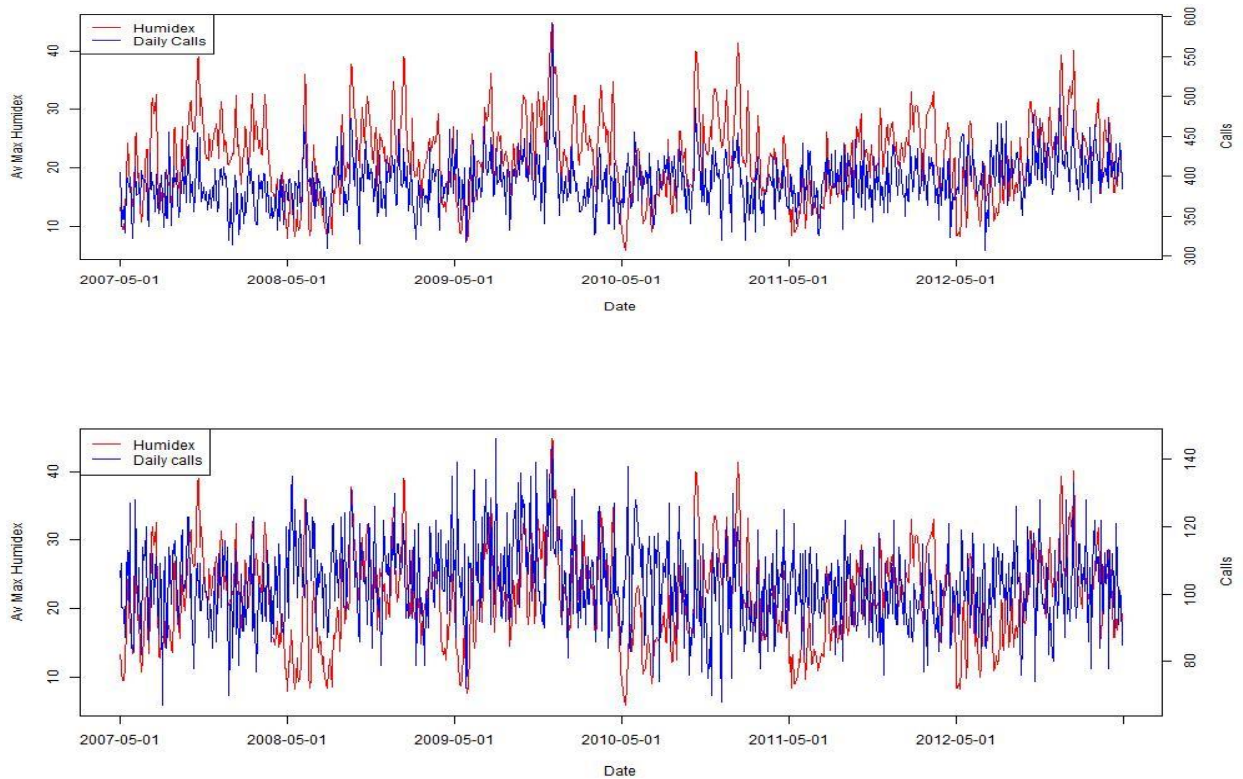
$$\log(\mu_j / \text{population}) = \beta_0 + \beta_1 I_j\{\text{humidex} > \text{threshold}\}$$

Where  $j$  indexes the day,  $\mu_j$  is the expected call count on day  $j$ , and  $I_j\{\text{humidex} > \text{threshold}\}$  is the indicator of a heat day, defined by its countywide average humidex exceeding a threshold.

Extreme heat can be defined as a threshold temperature chosen *a priori* or as a percentile of previously recorded temperatures for the specific study region. Since the latter definition is generally preferred to allow for location-specific variation of effects (EPA 2006), extreme heat was defined as the 90<sup>th</sup>, 95<sup>th</sup>, or 99<sup>th</sup> percentile of full year humidex values based on the Akaike Information Criterion (AIC) for the maximum likelihood best fit of the data within the model [Jackson et al. 2010; Medina-Ramon. et al. 2006; Vaidyanathan 2013]. Due to potential confounding of a percentile's selected threshold value by the seasonal time frame included in the analysis, full year humidex values were used for the threshold selection. However, analysis of

association between extreme heat and EMS calls was restricted to warmer months (May 1<sup>st</sup> through September 30<sup>th</sup>) so as to remove calls resulting from health conditions associated with cold temperatures and because there were no extreme heat days during those colder months [Alessandrini et al. 2011; Busch Isaksen et al. 2014<sup>1,2</sup>; Kue et al. 2013; Ng et al. 2014]. Days with average maximum humidex values at or above the selected threshold were defined as extreme heat days. For the BLS data, the 95<sup>th</sup> percentile (29.7 °C) provided the maximum likelihood of model fit, followed by 90<sup>th</sup> and 99<sup>th</sup>, but for the ALS data, the 99<sup>th</sup> percentile (36.7 °C) provided the maximum likelihood of model fit, followed by 95<sup>th</sup> and 90<sup>th</sup> percentiles.

**Figure 1: Combined trend plots of call counts and humidex for entire study timeframe. Top figure is for BLS data and bottom figure is for ALS data.**



Two characteristics of extreme heat were hypothesized to have the potential to increase or decrease the risk of an EMS call: the duration [Mastrangelo et al. 2007] of the extreme heat and the cooling down of temperatures at night [Schwartz 2005]. Heat duration was defined as a heat day's position in a consecutive series of heat days, the hypothesis being that as the heat increases in duration, the effects on health increase. The cool down effect was defined as the difference between average countywide high and low humidex for any day above the threshold. This effect was hypothesized to increase the effects of extreme heat on health with decreasing difference between high and low humidex. These characteristics were assessed for each data set on an all-ages, all-causes basis only using the statistical package "GAM" for RStudio version 0.97.449 [RStudio 2012]. Please see appendices 4 and 5 for additional detail.

## TIME-SERIES

The time-series (TS) approach modeled the relationship between average daily countywide maximum humidex values and EMS call rates using a nonparametric splining model with a piecewise linear fit with two knots. The first knot was set at the 50<sup>th</sup> percentile and the second, "optimum alert threshold", was set based on exploration of the data in 0.1 degree increments between 25°C and 44.7°C Humidex (the maximum humidex within the study timeframe). The time series equation is as follows:

$$Y_j \sim \text{Poisson}(P_j \mu_j), \text{ with}$$

$$\log(\mu_j) = \beta_0 + \beta_1(h_j - h_{q50})_+ + \beta_2(h_j - \hat{h}_0)_+ + s(t_j) + \sum_{l=6}^9 \beta_l I_{\{month=j-l\}}$$

Where  $Y_j$  is the observed EMS call count on day  $j$ ,  $P_j$  is the population on day  $j$ ,  $h_j$  is the county-wide average daily maximum humidex value on day  $j$ ,  $h_{q50}$  is the 50<sup>th</sup> percentile of Humidex from January 2007 through December 2012,  $h_0$  is the optimal alert threshold,  $s(t_j)$  is the

natural cubic spline modeling the overall trend of calls over 6 years,  $(\beta_i)$ 's) is a fixed effects adjustment for seasonal monthly effects,  $s(t_j)$  is the natural cubic spline modeling the overall trend of EMS calls over 6 years, and  $I_{\text{month}}$  is the indicator variable for months May through September.

Selection of the optimum alert threshold was based on the Akaike Information Criterion (AIC) for the maximum likelihood best fit of the model. Four models were considered for this analysis based on variables describing humidex values below or above the 50<sup>th</sup> percentile and below or above the threshold used in the relative risk analysis (95<sup>th</sup> or 99<sup>th</sup> percentile). Estimates of percent increases in daily EMS calls associated with one-degree increase above the optimum threshold were calculated using an intensity function.

Due to constraints of the EMS data, the analysis of effect modification was restricted to gender, but as with the relative risk analyses, effects from duration and cool down characteristics were also assessed as covariates. Please see appendices 6 and 7 for additional detail.

### **Cost Analysis**

The cost analysis quantified the impact of the association between extreme heat and EMS calls on county resources by providing a financial measure of comparison. Data used for this analysis included the average daily calls on heat days and non heat days from the relative risk analyses, as well as total call counts and total annual costs for BLS and ALS calls from the Public Health Seattle and King County Division of Emergency Medical Services 2012 Annual Report [PHSKC 2012]. Using data from this report, average costs for a BLS call and an ALS call were calculated and then applied to call counts from the relative risk analysis in Microsoft Excel Version 14.3.6 [Excel Mac 2011]. Please see appendix 8 for more detail.

## RESULTS

### Relative Risk Analysis

Significant results for all ages and by age group for all causes, non-trauma, and trauma are listed in Table 2. The risk of an EMS call on a heat day compared to a non-heat day increased for all causes, all ages in both the BLS and ALS analysis. The magnitude of this increase was greater for the ALS than the BLS data with an 8% (95% CIs: 6%, 9%) increase in calls on a 95<sup>th</sup> (29.7 °C) percentile heat day compared to a non heat day for the BLS data (420 vs. 390 average calls) and a 14% (95% CIs: 9%, 20%) increase on a 99<sup>th</sup> (36.7 °C) percentile heat day compared to a non heat day for the ALS data (117 vs. 103 average calls). Significant increases in risk were also detected in both analyses for non-trauma, all ages of 6% (95% CIs: 4%, 8%) for BLS data and of 13% (95% CIs: 7%, 19%) for the ALS. Significant results for trauma in all ages only resulted from the BLS analysis, where there was a 13% (95% CIs: 7%, 18%) increase in calls. Every age group had at least one analysis with statistically significant results: 15-44 and 45-64 year olds had the most consistent occurrence of significant increases in risk across all, trauma, and non-trauma causes and both datasets.

For subcategories of health effects, analyses of all ages revealed statistically significant increases in risk of a BLS call on a 95<sup>th</sup> percentile heat day compared to a non heat day of 4% (95% CIs: 0%, 8%) for abdominal/genito-urinary, 8% (95% CIs: 3%, 14%) for alcohol/drug, 14% (95% CIs: 2%, 27%) for anaphylaxis/allergy reaction, 11% (95% CIs: 4%, 18%) for metabolic/endocrine, 8% (95% CIs: 1%, 18%) for diabetes, 3% (95% CIs: 0%, 6%) for neurological, 17% (95% CIs: 13%, 20%) for other medical, and 243% (95% CIs: 7%, 284%) for heat illness and dehydration causes. By age group, all six groups identified statistically significant increases in risk in the other medical and heat and dehydration categories; 45-64 year

Table 2: Relative risk analysis results for BLS and ALS data. Data presented as increased risk (95% CIs) of an EMS call on a 95th percentile (29.7 °C) or a 99th percentile (36.7 °C) heat day compared to a non-heat day. Data displayed by age category for all causes, trauma, and non-trauma.<sup>1</sup>

		All Cause	Trauma	Non-Trauma
All Ages	BLS 95th	<b>1.08 (1.06, 1.09)</b>	<b>1.13 (1.07, 1.18)</b>	<b>1.06 (1.04, 1.08)</b>
	ALS 99th	<b>1.14 (1.09, 1.2)</b>	1.13 (0.91, 1.17)	<b>1.13 (1.07, 1.19)</b>
0-4	BLS 95th	<b>1.14 (1.07, 1.21)</b>	<b>1.35 (1.18, 1.54)</b>	<b>1.09 (1, 1.18)</b>
	ALS 99th	1.09 (0.82, 1.45)	1.47 (0.77, 2.79)	0.98 (0.7, 1.37)
5-14	BLS 95th	<b>1.07 (1, 1.14)</b>	1.11 (0.98, 1.25)	1.04 (0.95, 1.14)
	ALS 99th	0.78 (0.55, 1.11)	0.97 (0.46, 2.03)	<b>0.61 (0.38, 0.99)<sup>2</sup></b>
15-44	BLS 95th	<b>1.11 (1.08, 1.13)</b>	<b>1.16 (1.09, 1.23)</b>	<b>1.09 (1.06, 1.12)</b>
	ALS 99th	<b>1.18 (1.08, 1.28)</b>	1.17 (0.93, 1.47)	<b>1.13 (1.03, 1.25)</b>
45-64	BLS 95th	<b>1.09 (1.07, 1.12)</b>	<b>1.12 (1.05, 1.2)</b>	<b>1.07 (1.05, 1.1)</b>
	ALS 99th	<b>1.2 (1.11, 1.29)</b>	1.16 (0.83, 1.61)	<b>1.19 (1.1, 1.29)</b>
65-84	BLS 95th	<b>1.05 (1.03, 1.08)</b>	1.15 (0.97, 1.37)	<b>1.03 (1.01, 1.07)</b>
	ALS 99th	1.09 (0.99, 1.19)	0.87 (0.48, 1.55)	1.09 (0.99, 1.2)
85+	BLS 95th	1.02 (0.99, 1.05)	1.07 (0.89, 1.29)	1.02 (0.98, 1.06)
	ALS 99th	<b>1.13 (1, 1.26)</b>	0.75 (0.28, 2)	<b>1.13 (1, 1.27)</b>

olds had an increased risk from metabolic/endocrine, diabetes, alcohol/drug, and anaphylaxis/allergy reaction; 65-84 year olds had an increased risk for metabolic/endocrine and diabetes, 15-45 year olds were at increased risk from psychological and neurological effects, and 85+ were at increased risk for metabolic/endocrine effects. Please see table 9.2 in the appendix for more detail.

In the ALS data, the analysis of all ages identified a statistically significant increase in risk of an EMS call on a 99<sup>th</sup> percentile heat day compared to a non heat day of 23% (95% CIs: 5%, 45%) for abdominal/genito-urinary, 12% (95% CIs: 0%, 25%) for neurological, 39% (95% CIs: 25%, 53%) for other medical, and 607% (95% CIs: 438%, 830%) for heat illness and dehydration. Those 15-44 year olds were at increased risk for neurological, cardiovascular, and heat and dehydration effects; those 45-64 were at increased risk for other medical and heat and

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ )

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [1136 cases on non-heat days, 17 cases on a heat day]

dehydration effects; those 65-84 were at increased risk for other medical and heat and dehydration; and the 85+ age group was at increased risk of abdominal/genito-urinary, other medical, and heat and dehydration. Please see table 9.4 in the appendix for more detail.

No statistically significant association was found in either analysis for any age group for suspected CVA, seizures, febrile seizures, respiratory, and asthma health effects. Additionally, for the all ages group no association was found in any of the analyses for cardiovascular, psychological, OBGYN, and COPD health effects. The 0-4 year old category also showed no statistically significant results from the ALS data analysis.

Protective associations were detected for the BLS 95<sup>th</sup> percentile for suspected TIA for all ages and for the 85+ age group, as well as for COPD for the 85+ age group. The ALS analyses identified protective effects in the 5-14 year olds for non-trauma and neurological health effects. All protective effects resulted from analyses relying on very small sample sizes.

## TRANSPORTATION OUTCOMES

Significant changes in average call volumes can be found in table 3, while relative risk values are in table 9.5 in the appendix. Both BLS and ALS analyses identified significant increases in calls resulting in no transportation (11.4 and 2.6) and BLS transportation (15 and 7.2) for all ages; no transportation (4.9 and 1.2), ALS transportation (0.6 and 2.2), and other transportation (0.8 and 0.4) for 15-44 year olds; and BLS transportation for 45-64 year olds (5 and 2.8) as well as 65-84 year olds (1.9 and 1.9). Additionally, the BLS analysis identified significant results for all other age groups except the 5-14 year olds in no transportation, 0-4 year olds and 15-44 year olds in BLS transportation, and 65-84 year olds in other transportation. The

ALS analysis identified significant results for 85+ in BLS transportation and all ages in ALS transportation.

Table 3: Results for transportation outcomes for BLS and ALS data from the relative risk analyses. Data presented as the difference in average EMS call volumes ( $\Delta V$ ) on a 95th percentile (29.7 °C) or a 99th percentile (36.7 °C) heat day (HD) compared to a non-heat day (NHD) by age category.<sup>1</sup>

		No Transportation			BLS Transportation			ALS Transportation			Other Transportation		
		NHD	HD	$\Delta V$	NHD	HD	$\Delta V$	NHD	HD	$\Delta V$	NHD	HD	$\Delta V$
All Ages	BLS 95th	93.6	105.0	<b>11.4</b>	220.0	235.0	<b>15.0</b>	45.5	46.5	1.0	23.5	25.3	<b>1.8</b>
	ALS 99th	13.0	15.6	<b>2.6</b>	39.5	46.7	<b>7.2</b>	46.5	51.1	<b>4.6</b>	2.6	2.8	0.2
0-4	BLS 95th	4.3	5.1	<b>0.8</b>	3.6	4.2	<b>0.6</b>	1.0	1.0	0.0	2.0	2.1	0.1
	ALS 99th	0.3	0.5	0.2	0.7	0.9	0.2	1.0	1.1	0.1	0.3	0.1	-0.2
5-14	BLS 95th	4.4	4.7	0.3	4.9	5.2	0.3	0.7	0.7	0.0	2.1	2.2	0.1
	ALS 99th	0.4	0.2	-0.2	0.6	0.5	-0.1	0.7	0.7	0.0	0.1	0.0	-0.1
15-44	BLS 95th	33.3	38.2	<b>4.9</b>	69.8	76.5	<b>6.7</b>	10.2	10.8	<b>0.6</b>	9.6	10.4	<b>0.8</b>
	ALS 99th	3.7	4.8	<b>1.2</b>	10.1	10.5	0.4	10.4	12.6	<b>2.2</b>	0.8	1.2	<b>0.4</b>
45-64	BLS 95th	23.0	25.6	<b>2.6</b>	61.7	66.7	<b>5.0</b>	14.7	15.2	0.5	5.2	5.7	<b>0.5</b>
	ALS 99th	4.2	5.3	1.1	12.7	15.5	<b>2.8</b>	15.0	17.5	<b>2.5</b>	0.8	0.9	0.1
65-84	BLS 95th	18.6	20.2	<b>1.6</b>	50.1	52.0	<b>1.9</b>	13.4	13.3	-0.1	3.3	3.6	<b>0.3</b>
	ALS 99th	3.1	3.2	0.2	10.2	12.1	<b>1.9</b>	13.6	14.1	0.5	0.5	0.2	-0.3
85+	BLS 95th	10.1	10.7	<b>0.6</b>	29.9	30.0	0.1	5.7	5.5	-0.1	1.3	1.3	0.0
	ALS 99th	1.5	1.6	0.2	5.3	7.1	<b>1.8</b>	5.7	5.1	-0.6	0.2	0.4	0.2

## STUDY POWER

The six-year study timeframe included a total of 918 days with an average number of calls per day of 394 and 103 for BLS and ALS data, respectively. The sensitivity analysis for the removal of missing age and gender data demonstrated that removal of this data did not significantly impact the data for all ages and all causes given the two-sided p-value of 0.9928. However, both BLS and ALS data were weakened by diminished study power in many of the age categories and specific non-trauma cases, with many of the causes in the ALS data having less than 20 calls on all heat days combined (see table 9.8).

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ )

## EFFECTS OF HEAT CHARACTERISTICS

Analysis of the effects of heat duration and nighttime cooling revealed significant results for the BLS data only. With a total of 112 days above the 95<sup>th</sup> percentile and 23 days above the 99<sup>th</sup> percentile, the most frequent heat duration was one day (13 occurrences), followed by two days (11 occurrences), with a maximum of nine days (one occurrence in 2009). For all ages, all causes, there was an estimated change in calls of 0.01 calls per day of added duration (SE 0.004299). While consistent with the literature, this increase in effect is confounded by the increase in temperature on subsequent days within a multiday heat event. Please see figure 8.6 in the appendix. The analysis of cool down assessed for a change in effect associated with a change in average daily extremes (daytime high to nighttime low humidex). This analysis reported a range in the difference between average daily high and low humidex of 14.03 °C to 28.71 °C, with the difference increasing as average daily maximum humidex increased. Additionally, it should be noted that the average daily minimum humidex also increased as average daily maximum humidex increased. The estimated change in all age, all cause calls was 0.013 per degree increase in daily humidex difference (SE 0.003), demonstrating an increasing effect on health with increased cooling; a finding that is contrary to the hypothesis and existing literature [Schwartz 2005]. The most likely explanation of this is that increases in the average daily difference in humidex is confounded by increasing intensity of average daily maximum humidex, such that the increase in calls identified by the cool down analysis is an artifact of the increase maximum daily humidex rather than the cool down itself. Please see appendices 8 and 9 for more detail.

## Time Series Analysis

BLS and ALS analyses both contain statistically significant increases in EMS calls for every one-degree increase above their respective thresholds (40.7 °C for BLS and 39.7 °C for ALS data) for all causes, all ages; 6.6% (95% CIs: 4.5%, 8.7%) for BLS and 3.8% (95% CIs: 1.1%, 6.5%) for ALS. Additionally, both analyses identified significant results for all causes in 45-64 year olds; non-trauma in the all ages category; other medical for all ages, 15-44, 45-64, and 65-84 age groups; heat and dehydration in all ages, 15-44, 45-64, 65-84, and 85+ age groups; and emphysema/COPD in the 15-44 age group. The only additional statistically significant result for the ALS data was for OBGYN in the 45-64 age group. Please see table 4.

Significant results in the BLS data were found for all causes for all age groups; non trauma for all age groups excluding 0-4; metabolic for the 0-4 and 5-14 age groups; diabetes for the 15-44 age group; neurological for the 45-64 age group; suspected TIA for the 64-85 age group; febrile seizures for the 0-4 age group; other medical for the 0-4, 5-14, and 85+ age groups; psychological for all ages and the 5-14 and 45-64 age groups; and asthma for the 15-44 age group. The only cause that identified a protective effect in this analysis was trauma in the 15-44 age group. Causes with the most significant results were other medical, followed by all causes, and non-trauma and heat and dehydration. The age groups with the most significant results included 15-44 year olds, followed by all ages, 45-64 and 65-84, and 0-4, 5-14, and 85+.

Transportation outcomes showed an increase in no transportation above the respective thresholds for the BLS and ALS data, with both analyses producing significant results for all ages and the 15-44 and 45-64 age groups. BLS data identified significant results for no transportation in all but the 85+ age group. BLS transportation also identified relatively consistent increases in both analyses, with all ages and the 45-64 and 65-84 age groups

producing significant results. Additionally, the BLS data contained significant results for BLS transportation in the 15-44 and 85+ age groups. ALS data identified significant results for other transportation in the 85+ age group as well. Please see table 5.

Table 4: Time-series analysis results for BLS and ALS data. Percent changes in daily EMS calls presented for every 1 degree increase above 40.7 °C humidex for BLS and 39.7 °C humidex for ALS (95 CIs). Data displayed by age category and health outcome.<sup>1</sup>

Health Outcome	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
All Causes							
BLS	<b>6.6 (4.5, 8.7)</b>	<b>11.6 (1.7, 22.4)</b>	4.7 (-5.5, 15.9)	<b>5.1 (1.9, 8.3)</b>	<b>8.6 (5.3, 12.1)</b>	<b>7.6 (3.7, 11.7)</b>	<b>8.1 (2.9, 13.6)</b>
ALS	<b>3.76 (1.09, 6.5)</b>	4.2 (-11.1, 22.2)	2.1 (-16.8, 25.2)	1.9 (-3, 7)	<b>7.7 (3.5, 12.0)</b>	2.3 (-2.7, 7.5)	3.6 (-3.5, 11.2)
Trauma							
BLS	-4.3 (-10.2, 2.0)	3.4 (-17.2, 29.1)	14.5 (-33.9, 10.6)	<b>-11.5 (-20, -2.6)</b>	-2.9 (-13.1, 8.5)	4.5 (-7.1, 17.6)	7.0 (-8.1, 24.7)
ALS	-6.3 (-16.5, 5.3)	24.7 (-5.8, 65.2)	-4.7 (-44.8, 64.4)	-8.7 (-21.9, 6.7)	-8.5 (-28, 16.3)	-18.9 (-51, 34.0)	-2.1 (-45.3, 75)
Non-Trauma							
BLS	<b>10.0 (7.6, 12.5)</b>	-0.5 (-100, Inf)	<b>7.9 (4.5, 11.5)</b>	<b>10.9 (6.2, 15.8)</b>	-0.5 (-100, Inf)	<b>7.9 (4.5, 11.5)</b>	<b>10.9 (6.2, 15.8)</b>
ALS	<b>4.2 (1.3, 7.1)</b>	-7.1 (-26.1, 16.9)	-1.3 (-24, 28.2)	1.7 (-3.9, 7.6)	7.8 (3.5, 12.3)	2.2 (-2.9, 7.5)	4.2 (-2.9, 11.8)
Neurological							
BLS	<b>5.9 (1, 11.1)</b>	14.3 (-6.7, 39.9)	7.5 (-18.1, 41.0)	1.1 (-7.3, 10.3)	<b>11.2 (2.9, 20.2)</b>	5.0 (-4.1, 14.9)	3.3 (-8.9, 17.2)
ALS	5.43 (-0.97, 12.3)	-5.9 (-34.3, 34.9)	--	1.6 (-9.9, 14.5)	7.3 (-3.9, 19.8)	9.3 (-2.7, 22.7)	10.6 (-4.4, 27.9)
Other Medical							
BLS	<b>23.5 (19.6, 27.4)</b>	<b>31.3 (11.7, 54.4)<sup>2</sup></b>	<b>3.3 (21.5, 69.0)<sup>3</sup></b>	<b>25.1 (18.1, 32.6)</b>	<b>20.9 (14.2, 28)</b>	<b>22.1 (15.0, 29.7)</b>	<b>23 (14, 32.9)</b>
ALS	<b>18.3 (12.9, 23.9)</b>	1.2 (-35.9, 59.6)	27.5 (-17.5, 96.9)	<b>12.9 (0.6, 26.7)</b>	<b>20.6 (12.3, 29.5)</b>	<b>19.1 (9.3, 29.7)</b>	-9.6 (-46, 51)
Heat Illness & Dehydration							
BLS	<b>48.5 (39.9, 57.7)</b>	49.2 (-4, 131.9)	33.9 (-4.8, 88.3)	<b>48.1 (34.4, 63.1)</b>	<b>46 (31.2, 62.4)</b>	<b>42.1 (27.8, 58)</b>	<b>59 (39.9, 80.7)</b>
ALS	<b>48.9 (35.9, 63.1)</b>	-9.5 (-86.6, 512)	72.3 (1.3, 192.9)	<b>43.7 (16.5, 77)<sup>4</sup></b>	<b>50 (26.9, 77.2)<sup>5</sup></b>	<b>54.4 (32.2, 80.4)<sup>6</sup></b>	<b>41.4 (13.3, 77)<sup>7</sup></b>
Psychological							
BLS	<b>11.5 (4.1, 19.4)</b>	--	<b>42.6 (1.9, 99.5)<sup>8</sup></b>	6.6 (-3.3, 17.4)	<b>15.7 (3.3, 29.6)</b>	11.7 (-10.9, 39.9)	27.1 (-6.5, 72.9)
ALS	-4(-17, 11)	--	--	-9.8 (-28.5, 13.9)	4.5 (-14.5, 27.7)	-7.5 (-42.6, 48.9)	-6.9 (-60.8, 121.1)

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ )

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [1595 cases on non-heat days, 17 cases on a heat day]

<sup>3</sup> While statistically significant, the estimate is based on a small number of cases [1113 cases on non-heat days, 16 cases on a heat day]

<sup>4</sup> While statistically significant, the estimate is based on a small number of cases [79 cases on non-heat days, 7 cases on a heat day]

<sup>5</sup> While statistically significant, the estimate is based on a small number of cases [129 cases on non-heat days, 11 cases on a heat day]

<sup>6</sup> While statistically significant, the estimate is based on a small number of cases [160 cases on non-heat days, 18 cases on a heat day]

<sup>7</sup> While statistically significant, the estimate is based on a small number of cases [88 cases on non-heat days, 6 cases on a heat day]

<sup>8</sup> While statistically significant, the estimate is based on a small number of cases [411 cases on non-heat days, 4 cases on a heat day]

Table 5: Time-series analysis results for BLS and ALS data. Percent changes in daily EMS calls presented for every 1 degree increase above 40.7 °C humidex for BLS and 39.7 °C humidex for ALS (95 CIs). Data displayed by age category and level of transport. <sup>1</sup>							
Level of Transportation	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
No Transportation							
BLS	<b>10.9 (7.3, 14.6)</b>	<b>19.2 (5.6, 34.5)</b>	<b>18 (3.7, 34.3)</b>	<b>7.2 (1.8, 12.9)</b>	<b>16.0 (9.8, 22.6)</b>	<b>8.2 (0.7, 16.2)</b>	7.6 (-2.4, 18.7)
ALS	<b>10.0 (3.8, 16.6)</b>	15.7 (-15.3, 57.9)	10.9 (-22.1, 58.1)	<b>12.8 (3, 23.5)</b>	<b>12.8 (3, 23.5)</b>	3 (-10.6, 18.5)	-4.1 (-24.2, 21.2)
BLS Transport							
BLS	<b>7.0 (4.5, 9.7)</b>	9.0 (-6.9, 27.6)	-1.7 (-17.1, 16.6)	4.2 (0.1, 8.4)	<b>8.0 (3.8, 12.4)</b>	<b>8.9 (4.1, 14)</b>	<b>9.7 (3.5, 16.3)</b>
ALS	<b>7.2 (3.4, 11.2)</b>	3.2 (-22.1, 36.6)	-15.8 (-51.7, 46.9)	-0.6 (-8.2, 7.6)	<b>11.9 (5.7, 18.4)</b>	<b>8.2 (0.9, 16.1)</b>	9.3 (-0.6, 20.0)
ALS Transport							
BLS	-1.1 (-6.7, 4.8)	-1.7 (-31.1, 40.3)	13.5 (-18.5, 58)	-4.2 (-14.5, 7.4)	3.2 (-5.4, 12.5)	-2.7 (-12.3, 8.1)	-6.4 (-21.1, 11.0)
ALS	-1.4 (-5.5, 2.9)	-0.3 (-23.2, 29.3)	7.9 (-17.0, 40.3)	-3 (-10.7, 5.4)	1.8 (-4.6, 8.6)	-3.8 (-11.1, 4.2)	-4 (-14.6, 8.8)
Other Transport							
BLS	3.8 (-3, 11.0)	-11.7 (-34.9, 19.9)	-22.5 (-46.9, 13)	8.2 (-1.6, 18.9)	-7.9 (-22.1, 8.9)	15.9 (0.5, 33.7)	20.2 (-3.7, 50)
ALS	6 (-7.7, 21.8)	--	--	6 (-15.3, 32.6)	6.3 (-18.5, 38.6)	-2.1 (-33.3, 43.9)	<b>40.4 (5.4, 87.1)<sup>2</sup></b>

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ )

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [190 cases on non-heat days, 5 cases on a heat day]

## STUDY POWER

The time series analysis was considerably limited by study power. Due to the extremely high optimal threshold of 40.7 for the BLS data and 39.7 for the ALS data, the timeframe contained only 5 days above the threshold for the BLS data and 8 days above the threshold for ALS data. Combined with the lower number of daily calls in the ALS dataset compared to the BLS data set, the ALS analysis is particularly affected by study power, leaving only the most inclusive or greatest impact categories with enough calls to support the analysis. Statistically significant results with total call counts lower than 20 are reflected in Tables 4 and 5. Study could be improved with the inclusion of more years in the analysis or the selection of a lower optimal threshold.

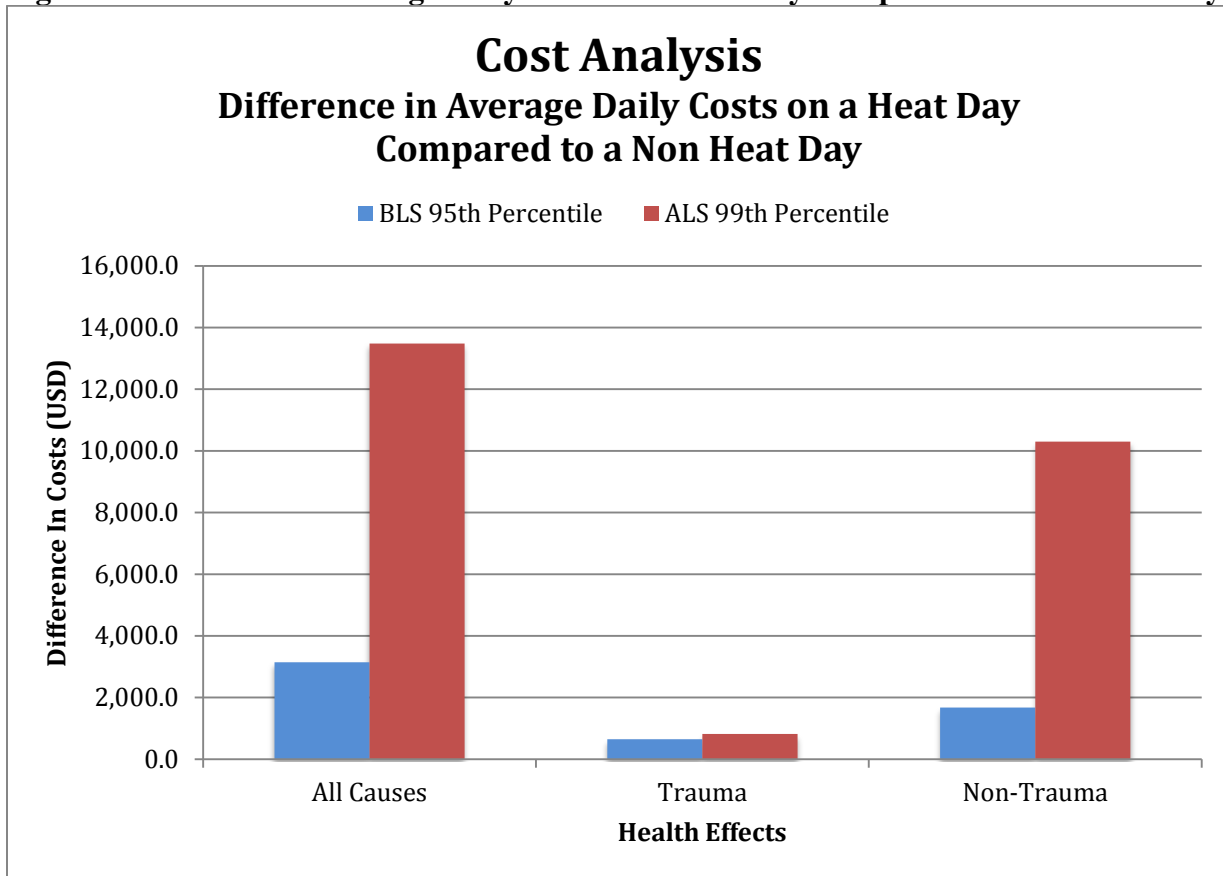
## EFFECTS OF HEAT CHARACTERISTICS

Analysis of the effects of extreme heat duration and nighttime cool down revealed no statistically significant changes in effect in either BLS or ALS analysis.

### **Cost Analysis**

On average, an ALS call cost approximately nine times that of a BLS call (\$963 and \$105, respectively) [PHSKC 2012]. Since increases in costs were the result of both the average call costs and average daily call counts, ALS calls had the greatest increases in cost for all causes, trauma, and non-trauma. For all causes and non-trauma, BLS calls had the lowest increases in costs (\$3,142 and \$1,676 respectively). Please see Figure 2. Please see appendix 11 for more detail.

**Figure 2: Difference in Average Daily Costs on a Heat Day Compared to a Non-Heat Day**



## DISCUSSION

The 8% (BLS) and 14% (ALS) increases in average EMS call volume on extreme heat days compared to non-heat days presented in this research are consistent with previous findings on the effects of heat on health within King County, WA and the existing EMS literature. [Busch Isaksen et al. 2014<sup>1,2</sup>; Dolney et al. 2006; Kue et al. 2013; Nitschke et al. 2011; Schaffer et al. 2012] The 6.6% and 3.8% increases in risk per degree increase in humidex for BLS and ALS data, respectively, from the time series analyses fall within the range of effects seen in other research and are reasonably similar to those reported by Alessandrini et al (2011) in Italy (8.85% increase in non trauma calls per degree increase above 30 °C). This is the first study to assess the

impact on BLS and ALS levels of EMS service separately, as well as the effects on EMS health outcomes by age group within a northern hemisphere population.

A central finding of this study is the striking increase in adverse health effects in an age-specific population that is consistent with effects identified in Australian EMS studies, but is significantly younger than previously reported for King County in other health datasets. Nitschke et al (2011) reported increases in risk of an EMS call-out in 15-64 year olds of 12% for all causes, 16% for cardiovascular, and 32% for respiratory illnesses during heat events consisting of 3 or more days above the 95<sup>th</sup> percentile (35 °C). While we have not identified increases in risk of respiratory illness, the only age group to experience cardiovascular effects was the 15-44 year olds of 29% at the 99<sup>th</sup> percentile (36.7 °C) in the ALS dataset. Recent hospitalization and mortality research for King County has primarily found increased risks associated with extreme heat for populations over 65 years of age [Busch Isaksen et al. 2014<sup>1,2</sup>; Jackson et al. 2010; Hansen et al. 2008; Knowlton et al. 2008]. This younger age group is of particular interest as it represents the working-aged population of 15-44 and 45-64 year olds who are often considered to be less vulnerable to heat than either the very young or very old. This is a significant finding that requires further investigation, as it demonstrates vulnerability in a high impact population. This finding may reflect hazards related to recreational or occupational activities, such as inadequate hydration and/or breaks [OSHA 2014] or increases in risk factors, such as obesity, that affect one's ability to thermoregulate [Buresh et al. 2005].

The analysis of transportation shows a general increase in both no transportation (12% for BLS and 20% for ALS) and transportation outcomes (combined 15% for BLS data and 28% for ALS data) that reflects the increase in calls on heat days, but does not show a dramatic preference for no transportation or transportation needs. The exception to this, where an analysis

identified increases in either no transportation or transportation outcomes (BLS, ALS, or Other) included no transportation for 85+ in the BLS analysis and transportation for 45-64 year olds and 85+ in the ALS analysis. The only other study to address EMS transportation separately from total calls found an increase of 24.8% during heat events consisting of 2 or more days at or above 32 °C, with a clear preference for transportation over no transportation [Kue et al. 2013]. While the results identified in this study do not reflect those in Kue et al. (2013), this variable does provide some insight into the impact on Emergency Rooms (ERs) where a gap in the regional health surveillance system currently exists. This gap is problematic as it excludes the population of individuals who are seen in the ER, but never get admitted to the hospital; quantifying EMS calls that result in transportation to hospital emergency rooms is one approach to measuring impacts on health at this level within the population. There are also cost and severity differences between BLS and ALS levels of transport, with BLS generally costing less and transporting less severe patients than ALS. The presence of consistent increases in BLS transports compared to ALS transports on heat days across different age groups and datasets is of particular interest due to the fact that BLS transports generally do not result in hospitalizations while ALS transports do. As a result, BLS transports are a better surrogate for the gap in ER data than ALS transports since the ALS transports would more commonly appear in hospitalization data while BLS would not.

The costs discussed in this study are of particular importance to county planning and resource management in light of the current inverse relationship between decreasing revenue and increasing expenditures. King County EMS receives most of its funding from a property tax levy. This revenue exceeded expenditures in 2008 by \$12 million, but has since declined so that combined with increased expenditures, 2013 experienced a \$5 million deficit. Short-term

projections by King County EMS predict this trend to continue with a widening deficit through 2019 [PHSKC 2014]. The estimated increase in costs associated with increased call volumes on heat days found in this study may seem inconsequential compared to the multi-million dollar annual EMS budget, but combined with the predicted increase in extreme heat frequency, severity, and duration associated with climate change trends, the impact on resources (personnel, equipment, etc.) and budget could increase significantly over time. In related research on mortality associated with extreme heat in King County, Isaksen et al. (2014) predicted increases of 2.3-8.0 and 4.0-22.3 times higher non-trauma mortality in their most affected age group by 2025 and 2045, respectively, compared to rates for 2002 through 2006. Should EMS calls experience a similar increase in volume in the coming years, this fiscal and resource dilemma may intensify if efforts are not made to prevent heat associated illness or find alternative sources of funding for the impacts of heat.

The extremely high optimal thresholds selected for the time series analyses raises some questions as to the practical implications for management and policy of the approach used to select these cutoffs. The thresholds of 40.7 °C humidex for BLS and 39.7 °C humidex for ALS were selected using the Akaike Information Criterion (AIC)—a selection method based on model best fit that is commonly relied on in statistical analyses. But given that both of these thresholds are considerably greater than even the 99<sup>th</sup> percentile of the humidex (36.7 °C), EMS data sample size is of concern and recommendations based on the intensities identified by these analyses would only be applicable a few days a year, if that. Since these high thresholds are largely the result of a few extreme hot days within the timeframe, the inclusion of a greater study period would likely attenuate these thresholds to a level that is more applicable to current management efforts. However, thresholds of this intensity may also be indicative of future trends in extreme

heat that, so they should not be completely discounted. Further investigation into the most appropriate approach to setting this optimal threshold should be considered so as to maximize both the scientific and practical applications of climate change epidemiology.

## **LIMITATIONS AND FURTHER RESEARCH**

While this study contains many strengths inherent to the analysis and available data, there were limitations associated with the data preparation, exposure misclassification, potential effect modification from co-exposures, and existence of multiple comparisons.

The presence of a high volume of missing data in the original dataset required removal of incomplete age and gender cases and limited the analysis to variables with the highest percent completion. Elimination of incomplete calls reduced the sample size by approximately 20% from both the BLS and ALS datasets. While the results of the sensitivity analysis indicated that the removal of these calls should not have impacted the association between extreme heat and EMS calls, it did reduce the sample size and thus the strength of specific health outcomes with small call volumes. High volumes of missing data in select variables of interest (e.g. property type) prohibited their inclusion in the analysis.

Misclassification of disease may exist in this dataset due to inherent differences in EMS identification of disease and physician diagnoses using the International Classification of Disease (ICD) codes; the main difference being that EMS responders do not diagnose, but rather identify the most likely medical condition based on signs, symptoms, and tools available in the field. Since some conditions present with similar symptoms (e.g. a circulatory condition may present with neurological signs and symptoms), the patient type variable was organized slightly different than the ICD codes. Nonetheless, the results are still highly applicable to public health

interpretation as well as EMS planning and preparation as they describe the patient's physical state resulting from the extreme heat.

EMS data is collected on a response-unit basis rather than a patient basis. This often results in the presence of duplicated entries for one EMS call that required merging for this analysis. This was executed by EMS personnel highly familiar with this practice, so the presence of duplicate entries should be minimal, but since not all units enter identical information for a given patient, limited duplication may exist. Additional limitations of the data result from the inability to assess the impacts of race/ethnicity and socioeconomic status since these variables were not available.

A final limitation of the dataset that may have influenced the results is the known occurrence of the use of private ambulance services among King County facilities catering to the elderly. As a result, this population may be underrepresented in the data. Future research should attempt to incorporate private ambulance services data whenever possible.

Averaging of exposure data across the geographic region and by calendar day introduced some exposure misclassification to the analysis. The geography of King County's 5,480 km<sup>2</sup> of land [US Census Bureau] varies with densely populated, sea level cities on the western edge and rural, forest covered mountains to the east. The use of a countywide average heat metric, therefore likely does not accurately represent the potential differences that may exist across this geographic region. Since high-resolution data was available, future studies should attempt to improve the precision of the exposure characterization by conducting the analysis on a cell-by-cell basis rather than county average. This study was not able to accomplish this due to sample size limitations of the EMS data containing geocoded locations. Precision could also have been

improved by refining the time unit to hours instead of days, but sample size limitations precluded this approach.

Air pollution was not incorporated into this study partially due to the lack of available data, but more so because it is not considered to be a confounder since it lies within the causal pathway of extreme heat and health and has a smaller effect size than that seen in the all-causes results of this study [Buckley et al. 2014].

The existence of multiple comparisons was not adjusted for in this study for two reasons. First, since this was a nested analysis, with sub-categories of health not independent of the non-trauma or all causes categories, it was not necessary to test for null of all tests. Second, while the use of a Bonferroni-type correction reduces type 1 error, it also increases type 2 error—the presence of which eliminates the hypothesis-driving aspect of the study and has negative implications for practitioners aiming to prevent the impacts of heat on health in their patients.

Future research should further evaluate the impacts of the duration and cool down effect present in the BLS analyses. Since the data used for this study collapsed calls on a daily basis rather than an hourly basis, these effects could not be further analyzed, but division of calls into cool and warm subsets of daily humidex fluctuations could shed further light on the impacts of extreme heat on health. Additionally, future research could evaluate the impact of occupational exposures or high exertion activities (e.g. youth sports leagues) on EMS call frequency with the inclusion of additional data.

## **CONCLUSIONS**

Extreme heat in King County, WA has a significant impact on emergency medical services as measured by increases in total calls, increases in transportation, and increases in costs

on heat days. The age-specific effects in 15-44 and 45-64 year olds demonstrate an impact on a population that has not been identified by other related studies in this region, but is consistent with other EMS studies. BLS and ALS transportation provide insight into the gap in regional health surveillance, with consistent increases in BLS transports to the emergency rooms across most age groups. The financial implications of these findings are important for county planning and resource management.

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# APPENDIX

## List Of Appendices

Appendix.....	47
1—Data Cleaning and Preparation.....	51
2—Data Cleaning and Preparation—R Code.....	67
3—Methods-Relative Risk Analysis.....	72
4—Methods-Relative Risk Analysis—R Code.....	76
5—Methods-Time Series Analysis.....	82
6—Methods-Time Series Analysis—R Code.....	85
7—Methods-Cost Analysis.....	98
8—Data Exploration.....	99
9—Results-Relative Risk Analysis.....	111
10—Results-Time Series Analysis.....	125
11—Results—Cost Analysis.....	131

**List of Tables**

1.1—Descriptive statistics for demographic data.....47

1.2—Descriptive statistics by gender, age, and age groups.....47

1.3—Descriptive statistics for age distribution of EMS data and King County population.....49

1.4—Descriptive statistics for location data.....50

1.5—Descriptive statistics of the breakdown of property use and location type data.....52

1.6—Descriptive statistics for medical treatment, outcome, and diagnosis information, not including procedures and flow chart data.....53

1.7—Descriptive statistics of specific health outcomes-IDC.....55

1.8—Descriptive statistics of specific health outcomes-Patient Type.....57

1.9—Descriptive statistics for procedure codes.....58

1.10—Descriptive statistics for flow chart data.....59

1.11—Descriptive statistics of the breakdown of treatment data.....60

4.1—Mean and max Humidex by summer month for study period.....70

4.2—Humidex percentiles and model fit.....71

9.1—RR for BLS and ALS for all cause, trauma, and non-trauma.....111

9.2—RR for BLS data at 95<sup>th</sup> percentile.....112

9.3— RR for BLS data at 99<sup>th</sup> percentile.....113

9.4— RR for ALS data at 99<sup>th</sup> percentile.....115

9.5—RR for BLS and ALS for transportation.....116

9.6—Call count for BLS and ALS transportation.....117

9.7—Total call counts for BLS data at 95 <sup>th</sup> percentile.....	119
9.8—Total call counts for BLS data at 99 <sup>th</sup> percentile.....	120
9.9—Total call counts for ALS data at 99 <sup>th</sup> percentile.....	121
9.10—Average call counts for BLS and ALS data.....	120
9.11—Duration and cool down effects.....	123
9.12—Sensitivity Analysis.....	123
10.1—Time series analysis result for BLS data for health outcomes.....	127
10.2—Time series analysis results for ALS data for health outcomes.....	128
10.3—Time series analysis results for BLS and ALS data for transportation.....	129
11.1—Analysis of EMS call costs.....	13

## List of Figures

8.1—Scatterplots of King County EMS calls per day by humidex.....	101
8.2—Scatterplot of King County EMS calls per day by humidex for BLS data with 2 knots....	102
8.3—Combined trend plots of call counts and humidex for entire study timeframe.....	103
8.4—Average maximum humidex for King County in 2009.....	104
8.5—Duration effects.....	105
8.6—Duration effects.....	106
8.7—Cool down effects.....	107
8.8—Cool down effects.....	108
8.9—Cool down effects.....	108
8.10—Fine tuning the model.....	109
8.11—Time Series analysis threshold selection.....	110
11.1— Difference in Average Daily Costs on a Heat Day Compared to a Non-Heat Day.....	132

## **APPENDIX 1:**

### **DATA CLEANING AND PREPARATION**

The following appendix describes the methods used to create the final Emergency Medical Services (EMS) dataset for the regression analysis of the impacts of extreme heat on EMS calls in King County, WA. Data was provided by King County Emergency Medical Services with the approval of the University of Washington's Human Subjects Division. This appendix does not discuss any data preparation steps conducted by King County EMS employees to remove duplicate call entries. The discussion of the methods includes not only the specific steps taken, but also justifications for those steps. This report does not include specific placement for most quality assurance and control measures as this was checked repeatedly throughout each step of the cleaning and preparation processes. The processes described for restricting the dataset to non-missing age and gender data gives an example of how QA/QC is used throughout the process. Tables summarizing descriptive statistics for the entirety of the final dataset as well as Humidex values for the study time frame (2007-2012) are included throughout this appendix. Preparation and cleaning of the data is discussed in four sections; variables not included in any of the four sections have not been directly altered, but may have been affected by steps taken to clean other variables.

- 1) Restricting the dataset to non-missing age and gender data
- 2) Preparing demographic variables: Age, Gender, and Time.
- 3) Preparing location specific variables: Property Use and Location Type
- 4) Preparing health outcome variables: IDC, Patient Type, Procedure, Flow Chart, Transportation Destination, Transport Level, and Action Taken.

## Tables

- 1.1—Descriptive statistics for demographic data
- 1.2—Descriptive statistics by gender, age, and age groups
- 1.3—Descriptive statistics for age distribution of EMS data and King County population
- 1.4—Descriptive statistics for location data
- 1.5—Descriptive statistics of the breakdown of property use and location type data
- 1.6—Descriptive statistics for medical treatment, outcome, and diagnosis information, not including procedures and flow chart data
- 1.7—Descriptive statistics of specific health outcomes-IDC
- 1.8—Descriptive statistics of specific health outcomes-Patient Type
- 1.9—Descriptive statistics for procedure codes
- 1.10—Descriptive statistics for flow chart data
- 1.11—Descriptive statistics of the breakdown of treatment data

## **Restricting The Dataset To Non-Missing Age And Gender Data**

### AGE DATA

The decision to exclude missing age data was motivated by other recent, related research by Busch Isaksen et al. (2014) that demonstrates effect modification of age on the association between extreme heat and health outcomes. Since age cannot be interpolated, missing data was excluded from the analysis. This eliminated 14% of the BLS and 18% of the ALS EMS calls. This process started with running descriptive statistics on PatientAgeYears as a QC measure.

Next, a duplicate dataset was created (“BLS”) to allow for manipulation of variables without interfering with the remainder of the code should someone want to run statistics on the data without excluding missing age or gender. This step also provided some room for error while developing the correct code without requiring reloading the data after each failed attempt. With this duplicate dataset, all missing values were recoded as -1 to match the age variable’s coded value for missing data and in preparation for the selected approach used to restricting the dataset. Using the recoded age variable in the duplicate dataset, a subset of the data was created where all PatientAgeYears are greater than or equal to 0; this subset replaced the original dataset (“emsBLS”). Subsequently, descriptive statistics were run as a QC measure.

Excluding age decreased the BLS sample size from 441119 to 377388 with a reduction in calls missing gender from 17% of the data to 4%. For ALS data, the sample size decreases from 121974 to 99,329 with a reduction in calls missing gender from 20% to 5%.

## GENDER DATA

Exclusion of EMS calls missing gender data followed a similar process to exclusion of missing age data. The process differed in the integer used by the gender variable for missing EMS calls (9 instead of -1) as well as the inclusion of age parameters (e.g.  $\geq 0$ ) in the subsetting process. Excluding missing gender data reduced the BLS sample size from 377,388 to 361,434 and reduced the ALS sample size from 99,329 to 94,565. Calls per day for BLS data were reduced to 393 and to 103 for ALS data.

Additional benefits from excluding missing age and gender data included the reduction in missing data from other variables. This primarily affected the Transport Destination Category and Transport Level variables where missing data decreased in both variables from 12% and 16% to 2% and 1% for BLS and ALS, respectively. Missing data in Action Taken, Highest Level Care Received, and Patient Type Code variables also decreased. Within the Patient Type Code variable, EMS calls coded as “other-non diagnostic” decreased from 16% of the data for both BLS and ALS to 6% for BLS and 2% for ALS.

## **Demographic Variables: Age, Gender, And Time.**

### AGE DATA

Patient ages spanned approximately 110 years, with infants coded as 0 years old and the oldest BLS and ALS patients having ages of 110 and 109 years, respectively. To improve

statistical power and provide an additional level of protection to patient identities, ages were grouped into categories based on previously used cutoffs [Busch Isaksen et al. 2014]. Two groups of categorized ages were created for the analysis: one with 6 categories and one with 3. The 6 categories include 0-4, 5-14, 15-44, 45-64, 65-84, and 85+, while the 3 categories group all ages from 0-64 together, leaving the 65-84 and 85+ categories as is.

Table 1.1: Descriptive statistics for demographic data. Statistics include n, % missing, # of unique variables, and mean values for age, gender, and calls per day for BLS and ALS data.

Demographics	Count		% Missing		Unique		Mean	
	BLS	ALS	BLS	ALS	BLS	ALS	BLS	ALS
StudyID	361434	94565	0	0	361434	94565		
Incident Date	361434	94565	0	0	918	918	393 calls/day	103 calls/day
AgencyTypeKCEMS	361434	94565	0	0	1	3		
AgencyNumberKCEMS	361434	94565	0	0	32	47		
Patient Age Years	361434	94565	0	0	111	110	52.5 years	56.7 years
PatientGenderID	361434	94565	0	0	2	2	1.516	1.484
PatientNumber	361275	94514	0	0	17	10		

Table 1.2: Descriptive statistics for gender, age, and age groups for both BLS and ALS. Statistics include number of observations (n), percent missing (% missing), and mean, min, and max values for age and gender.

Demographics	n(%missing)		% of total		Mean(min, max)	
	BLS	ALS	BLS	ALS	BLS	ALS
Gender	361434(0)	94565(0)			1.52	1.484
Male	174667	48779	48	52		
Female	186767	45786	52	48		
Age	361434(0)	94565(0)			53 (0, 110)	57(0, 109)
0-4	10436	2141	3	2	3	4
5-14	11414	1654	3	2	6	5
15-44	116587	23194	32	25	42	51
45-64	9887	30426	27	32	23	25
65-84	80221	25407	22	27	15	10
85+	43899	11743	12	12	11	4

Table 1c in the Appendix includes additional information not from this dataset regarding the age distribution of King County’s population from 2007 to 2012. This data is included in this analysis to provide background information regarding the geographic population in which the EMS calls are drawn from. Contextual information of this sort may be beneficial when applying results to other regions with a different background population distribution as well as when planning for expected future populations. This data was from the Office of Financial

Management (OFM) [OFM 2012; OFM 2013] and required some minor preparation from its original form since it included annual population counts in 5-year age increments. In order to provide the population counts in terms of the age groups used for this study, the population counts were added across the study’s timeframe (2007-2012), summed into the 6 age groups used for this study, and then divided by the total population. The population distribution for all of King County differs from the distribution within all EMS calls in a manner that is consistent with what one would expect given the characteristic relationship of age to the number and severity of an individual’s medical concerns. For all of King County, 63% of the population was younger than 45 and 11% was 65 or older, but in the EMS BLS data only 38% was younger than 45 and 34% was 65 or older. When only comparing the trauma patients to the county’s background population distribution, this difference lessens with 51% of BLS trauma patients under the age of 45 and 26% 65 years or older.

## GENDER DATA

Gender data was coded numerically as 1 for male and 2 for female. An additional variable coded gender as “male” and “female” provides cleaner table and figure output.

Table 1.3: Descriptive statistics of age distribution of EMS data and King County data. EMS data is displayed for all calls and for trauma calls only. County data is sourced from the Office of Financial Management. All statistics are percentages (%) of the total (calls, trauma calls, or population) for 2007-2012.					
Age	All Calls %		King County Population %	Trauma Only %	
	BLS	ALS		BLS	ALS
0-4	3	2	6	3	4
5-14	3	2	12	6	5
15-44	32	25	45	42	51
45-64	27	32	27	23	25
65-84	22	27	9	15	10
85+	12	12	2	11	4

## TIME

The study's timeframe included the warmer months, May 1<sup>st</sup> through September 30<sup>th</sup>, over a 6 year period, 2007-2012. Since the data was stored in a date format of year-month-day, additional variables allowing for the selection of EMS calls by year and month allowed for additional approaches to analyzing the call data and were necessary for the humidex modeling.

## Location Specific Variables: Property Use And Location Type

There were two variables describing the use or type of location where an EMS call was generated; property use and location type. Additional variables describing location included geocoding, latitude, and longitude. Please see table 1.4 for general descriptive statistics.

Location	Count		% Missing		Unique	
	BLS	ALS	BLS	ALS	BLS	ALS
GeocodeAux	358316	94213	1	0	3603	3227
Latitude	208479	70372	42	26	23984	17209
Longitude	208472	70373	42	26	28909	17947
PropertyUse	206742	29598	43	69	176	134
PropGroups	206742	29598	43	69	10	10
LocationTypeID	321154	83717	11	11	15	14

## PROPERTY USE

The property use variable contained 176 (BLS) and 134 (ALS) unique values that fall within 10 higher levels of property uses. To simplify and improve statistical power, the unique values were collapsed into the 10 more generalizable groups. Two components of the variable's structure were important for this procedure: the variable's data class in programming software (e.g. R) and the EMS-designated structure of the codes used for each unique level in relation to

the 10 higher levels. In its original form, this variable was a factor type variable in R. As such it was difficult to work with and needed to be converted to a character class. The format of the unique levels and the 10 higher groups was designed so that each code was a specific number between 100 and 999, with each higher group starting with the same first number. There were a few exceptions to this coding convention that result in the formation of the 10<sup>th</sup> group; these exceptions all started with letters and there are relatively few of them.

It was the opinion of this researcher that this variable as not of significant value to this research due to the quantity of missing entries and existence of a very similar variable, Location Type. It is possible, however, that select groups may demonstrate their value at a later time due to the highly specific nature of the individual codes within the groups. One example of this was the Health Care, Detention, and Correction group.

## LOCATION TYPE

The location type variable was classed as an integer and consisted of 12 codes for specific location types, 1 code for other locations, and 1 code for unknown locations. It should be noted that prior to excluding missing age and gender from the dataset, this variable did contain two codes that were likely data entry errors as they were not included in the data dictionary and were very rarely seen. These codes were eliminated as a result of excluding missing age and gender data. Data preparation of this variable consists of creating a new variable where each code was recoded with the description of the location type used in the data dictionary.

While the location type data did not include codes with any greater level of detail than those above, the full data dictionary provided by King County EMS did include examples of locations that fell within each specific type. Of greatest benefit to understanding this variable

was the list of locations included as “other location”. This group primarily included outdoor locations not otherwise specified (NOS) such as beach NOS, canal, caravan site NOS, derelict house, desert, dock, forest, harbor, hill, lake NOS, mountain, parking lot, parking place, pond or pool (natural), prairie, public place NOS, railway line, river, seas, seashore NOS, stream, swamp, trailer court, and woods.

### Health Outcome Variables: IDC, Patient Type, Procedure, Flow Chart, Transportation Destination, Transport Level, And Action Taken

There were three main types of health outcome variables. The first type described the main reason the patient required emergency medical services and included the initial

Table 1.5: Descriptive statistics of the breakdown of property use and location type data. Statistics include number of observations (n), percent missing (% missing), % of total for a given group.

Location	n(%missing)		% of total	
	BLS	ALS	BLS	ALS
PropertyUse (by grouping)	206742(43)	29598(68)		
Assembly	9102	912	4	3
Education	3274	335	2	1
HealthCare, Detention, Correction	25778	5449	12	18
Industrial, Utility, Defense, Ag.	254	50	0	0
Manuf., Processing	628	55	0	0
Mercantile, Business, Other	10463	1409	5	5
Other	298	59	0	0
Outside or Special Property	33551	2863	16	10
Residential	120018	17581	58	59
Storage	3376	885	2	3
LocationType	321153(11)	83717(12)		
Adult Family Home	7851	1819	2	2
Educational Institution	3405	383	1	0
Farm	161	47	0	0
Highway	7700	1139	2	1
Industrial Place	3939	1069	1	1
Medical Facility	8041	4307	3	5
Mine/Quarry	8	2	0	0
Nursing Home	17046	5320	5	6
Other location	54862	14574	17	17
Public Building	16705	2991	5	4
Recreation or Sports Facility	2635	498	1	1
Residence	172312	47981	54	57
Street	26396	3335	8	4
Unknown	92	252	0	0

dispatch code (IDC) and patient type. These variables are most easily comparable to an EMS version of the International Classification of Disease (ICD) codes used in hospital settings to diagnose patients. The next type of variable described a procedure that was performed at the scene to treat or track the patient's health and included procedure codes and flow chart codes. The last group described the overall level of medical treatment necessary for the patient, including transportation or calling a higher level of care to the scene. These variables included transportation destination, transport level, action taken, and highest level of care received. Corresponding tables include 1.6, 1.7, 1.8, and 1.9.

Health Outcome	Count		% Missing		Unique	
	BLS	ALS	BLS	ALS	BLS	ALS
IncidentType	345463	94487	4	0	102	50
Primary Medical Concern						
InitialDispatchCode	236607	51566	35	45	902	527
IDC	225049	51566	38	45	26	26
PatientTypeCode	353731	93793	2	1	312	235
PtType	309385	90579	14	4	12	12
Level of Treatment						
TransportDestinationCategory	354421	93583	2	1	6	6
TransportLevel	354526	93608	2	1	4	4
ActionTaken	292198	85051	19	10	7	7
HighestLevelCareReceived	273305	79011	24	16	7	5

### INITIAL DISPATCH CODE (IDC)

EMS dispatchers assign the initial dispatch code (IDC) to each call based on the information they received through the 911 call. It was used in part to help determine what level of response should be sent to the scene, but also as a method of providing information to the EMS responders regarding the medical situation they should expect upon arrival at the scene (please see Table 3b). Since there were 447 permissible values, the 902 and 527 unique values in

the BLS and ALS datasets, respectively, indicate the existence of potentially significant missing values due to data entry error most likely attributable to agencies that have not yet transitioned to electronic forms. The 447 permissible values can, however, be collapsed into 27 high levels. As with the property type variable, two components of the variable's structure were important for this procedure: the variable's class and the format of the codes used for each unique level in relation to the 27 higher levels. In its original form, this variable was also a factor and required conversion to a character class.

The format of the unique levels and 27 higher classifications of this variable were somewhat more complex than the property type variable and required additional steps for an accurate collapse of the groups. The coding of this variable included three specific positions; the first position held a number (1-26) indicating the higher classification, the second position held a single letter (M, P, Q, R, Y, or T) indicating the severity of the situation, and the third position held another number indicating a specific medical issue within the higher classification. In order to accurately select groups of levels that start with similar numbers (i.e. only group 1 and not groups 1 plus 10-19), the general expression used to select the data need to couple the first number with the middle position as an indication that the first number was complete. To accomplish this cleanly, a variable was created that replaced any of the six possible second position letters with an underscore. Then, using this new format, unique levels were selected by searching for the group's number followed by the underscore.

It was the opinion of this researcher that this variable was not of significant value to this research due to the quantity of missing entries and existence of a very similar variable, Patient Type. It was possible, however, that select groups may demonstrate their value at a later time due to the highly specific nature of the individual codes within the groups.

## PATIENT TYPE

The patient type variable was assigned by the EMS responder as the medical condition of highest concern or the primary reason for the call. Since this variable contained 228 permissible values, the 312 and 235 unique values in the BLS and ALS datasets, respectively, indicated the presence of data entry error similar to that in the

Table 1.7: Descriptive statistics of specific health outcomes for BLS and ALS data under the IDC variable. Statistics include number of observations (n), percent missing (% missing), % of total for a given group.

Medical Issue	n(% missing)		% of total	
	BLS	ALS	BLS	ALS
IDC Group	225049(38)	48732(49)		
Abdominal/Back/Groin Pain	15697	1044	7	2
Anaphylaxis/Allergic Reaction	3059	636	1	1
Animal Bites	580	15	0	0
Assault Trauma	9954	704	4	1
Bleeding	5580	480	2	1
Breathing Difficulty	18314	6974	8	14
Burns-Thermal/Electric/Chemical	585	118	0	0
Cardiac Arrest	2909	1252	1	3
Chest Discomfort/Heart Problems	24480	15941	11	33
Choking	1268	126	1	0
Diabetic	8215	3002	4	6
Drowning/Near Drowning/Diving or Water Related	160	69	0	0
Environmental/Toxic Exposure	624	58	0	0
Falls/Accidents/Pain	39673	2119	18	4
Head/Neck	3204	277	1	1
Infectious Disease	10	3	0	0
Medical Knowledge	2392	1434	1	3
Mental/Emotional/Psychological	4937	225	2	0
Motor Vehicle Accidents (MVA)	17671	2116	8	4
OD/Poisoning	8296	1552	4	3
Pediatric Emergency	2460	515	1	1
Pregnancy/Childbirth/GYN	1703	286	1	1
Seizures	7620	1824	3	4
Sick (unknown)/Other	26739	3251	12	7
Stroke (CVA)	7349	1026	3	2
Unconscious/Unresponsive/Syncope/Weak	11570	3685	5	8

IDC variable. The 228 permissible values could however be collapsed into 12 higher categories for better summarization and statistical power (please see Table 3c).

The first step in collapsing this variable was to create a duplicate variable where the class

was changed from a factor to a character.

With the new variable, groups of values were selected and recoded with the name of the higher classification. Due to the presence of erroneous values, all permissible codes needed to be specifically indicated for each group.

In order to better analyze the impacts of extreme heat on specific health outcomes, an additional variable was created for each of the above groups, as well as one for all non-traumatic outcomes (excluding the Other-Non Diagnostic group). Given the specific focus of this research and findings from Busch Isaksen et al.'s (2014) recent work, variables were also created for certain unique values, or groups of values, that were of additional interest. These additional values include:

- Heat Illness and Dehydration
- Diabetes
- Suspected cerebrovascular accident(CVA)
- Suspected traumatic ischemic attack (TIA)
- Asthma
- Emphysema/COPD

Likely due to how emergency response care does not truly diagnose conditions, but rather focus on treating a patient's signs and symptoms, some health conditions of interest were not available in this data or were classified differently than they would be in a hospital setting. For example, a circulatory condition may present with neurological signs that could be attributed to that circulatory condition or to another condition that was in fact neurological.

- Nephritis & nephrotic issues as well as acute renal failure were not included
- Heat Illness was considered medical rather than traumatic

- CVA and TIA were classified under neurological rather than circulatory
- Patient type codes for trauma were specific to the body part and type of injury, not the cause. Therefore, trauma does not include mention of accident, suicide, or homicide. A mechanism code does exist that includes “accident” but it is not included in this dataset. Suicide and homicide were mentioned no where in the PDF data dictionary provided for all collected variables

These additional variables were created by selecting groups from the PtType variable above or specific values from the PtTypex variable. Once selected, these values were replaced with a “1” when present and a “0” when not present.

Table 1.8: Descriptive statistics of specific health outcomes for BLS and ALS data under the Patient Type variable. Statistics include number of observations (n), percent missing (% missing), % of total for a given group.

Medical Issue	n(% missing)		% of total	
	BLS	ALS	BLS	ALS
Patient Type - All Calls	309385(14)	90579(4)	100	100
Non-Trauma	238045	82232	77	91
Abdominal/Genito-Urinary	26452	5172	7	6
Alcohol/Drugs	17353	4253	5	5
Anaphylaxis/Allergic Reaction	3515	1145	1	1
Cardiovascular	30259	24130	9	27
Metabolic/Endocrine	9439	4286	3	5
Diabetes	7075	3841	2	4
Neurological	47986	13551	14	15
Suspected CVA	6432	1354	2	1
Suspected TIA	694	68	0	0
OBGYN	2854	992	1	1
Other Medical	58164	14324	16	16
Heat Illness & Dehydration	3400	514	1	1
Psychological	18149	3267	5	4
Respiratory	23874	11112	7	12
Asthma	1130	583	0	1
Emphysema/COPD	812	580	0	1
Trauma	47005	6127	15	7
Other-Non Diagnostic	24335	2220	6	2

## PROCEDURE & FLOW CHART CODES

All procedure variables and one flow chart variable contained 2 unique values, “yes” and “no”. The original coding of these variables designated 1 for “yes” and 2 for “no”, but since it is generally preferable for “no” to be coded as 0 rather than 2, the 41 procedure codes required recoding. Rather than manually recoding each procedure variable, a general expression was used to select each variable starting with “Proc” and return the placement of that column in the dataset. Please see table 1.9.

Using the returned column placements of the procedure variables and the lapply function in R, all values of 2 were recoded as 0.

Table 1.9: Descriptive statistics for medical procedures. Statistics include number of patients who received the procedure (n), percent of patients not receiving the procedure (%), and number of unique variables.						
Medical Procedures	Yes Proc (n)		No Proc (%)		Unique	
	<i>BLS</i>	<i>ALS</i>	<i>BLS</i>	<i>AL</i> <i>S</i>	<i>BL</i> <i>S</i>	<i>AL</i> <i>S</i>
Proc00_None	5805	808	98	99	2	2
Proc01_Oxygen	98168	71074	73	25	2	2
Proc02_WoundCare	18730	2241	95	98	2	2
Proc03_Extrication	750	555	100	99	2	2
Proc04_Splinting	10094	1984	97	98	2	2
Proc05_Bagvalve	2811	4716	99	95	2	2
Proc06_ECGMonitor	41792	58087	88	39	2	2
Proc07_CCollarORBackboard	8739	3343	98	96	2	2
Proc08_CPRPerformed	1145	1661	100	98	2	2
Proc09_PlanA1	11	33	100	100	2	1
Proc10_PlanA2	0	0	100	100	1	1
Proc11_PlanB	0	0	100	100	1	1
Proc12_EndotrachealIntubation	2287	5278	99	94	2	2
Proc13_IVCentralLine	59	780	100	99	2	2
Proc14_IVPeripheral	22970	41957	94	56	2	2
Proc15_ManDCShockbyEMT	118	92	100	100	2	2
Proc16_IntracardiacInjection	23	25	100	100	2	2
Proc17_FlutterValve	11	110	100	100	2	2
Proc18_Pericardiocentesis	1	33	100	100	2	2
Proc19_Cricothyrotomy	27	29	100	100	2	2
Proc20_NeedleCricothyrotomy	0	0	100	100	1	1
Proc21_AutoDCShockbyEMT	217	119	100	100	2	2
Proc22_IntraosseousLine	78	231	100	100	2	2
Proc23_ExternalPacing	28	38	100	100	2	2

Proc24_FirstResponderDCShock	14	91	100	100	2	2
Proc25_AEDAttNoShock	4320	2165	99	98	2	2
Proc26_RetrogradeIntubation	0	0	100	100	1	1
Proc27_JetINSufflation	0	3	100	100	1	2
Proc28_AssistedPtOwnMeds	76	14	100	100	2	2
Proc29_EpipenUsed	64	32	100	100	2	2
Proc30_Cardioversion	4	24	100	100	2	2
Proc31_Glucometry	27073	18608	93	80	2	2
Proc36_12LeadECG	6691	14024	98	85	2	2
Proc37_EndTidalCO2	3113	3671	99	96	2	2
Proc54_PulseOximetry	63279	30185	82	68	2	2
Proc57_Temperature	0	0	100	100	1	1
Proc70_OG_NGTube	0	90	100	100	1	2
Proc71_Escharotomy	0	1006	100	99	1	2
Proc72_Episiotomy	0	0	100	100	1	1
Proc73_Childbirth	0	15	100	100	1	2
Proc99_Other	0	0	100	100	1	1

Since the flow chart variable had a different prefix than the procedure variables, the selection command did not apply and a new selection command was not necessary since there was only one flow chart variable requiring recoding. This variable was recoded manually using a direct recode command. Please see table 1.10.

Table 1.10: Descriptive statistics for flow chart entries. Statistics include number of patients who received the procedure (n), percent of patients not receiving the procedure (%), and number of unique variables for BLS and ALS data. *binary variable. N displayed as sum of positive answers.						
Flow Chart Entries	Count		% Missing		Unique	
	BLS	ALS	BLS	ALS	BLS	ALS
FC_DCShock	2	0	100	100	2	0
FC_DiastolicBP	236098	66723	35	29	220	168
FC_DiastolicPalp*	37648	7235	90	92	2	2
FC_ECGRhythmID	13680	24620	96	74	85	13
FC_GlucoseLevel_Final	1652	1178	100	99	359	338
FC_GlucoseLevel_Initial	31187	15753	91	83	580	497
FC_IVFluidVolume	0	6799	100	93		94
FC_MedsAdministered	7064	7870	98	92	525	1444
FC_OxygenRate	7326	13877	98	85	52	33
FC_PulseOximetry	70937	22500	80	76	123	72
FC_PulseRate	305433	83331	15	12	249	239
FC_RespiratoryRate	197669	79926	45	15	128	90
FC_VitalSignsHR	197666	49064	45	48	32	24
FC_VitalSignsMin	197665	49064	45	48	70	60
FC_VitalSignsPostureID	262042	57033	27	40	6	6

## TRANSPORTATION DESTINATION, TRANSPORT LEVEL, & ACTION TAKEN

Transportation destination, transport level, and action taken all contained a unique value of -1 for missing data. Since the rest of the variables in the dataset did not contain this coding structure or have had their missing values removed from the dataset, the values of -1 were recoded as “NA”. This ensures there was a consistent response for missing values. Please see Table 1.11.

Table 1.11: Descriptive statistics of treatment outcomes for BLS and ALS data. Statistics include number of observations (n), percent missing (% missing), % of total for a given group.				
Treatment	n(% missing)		% of total	
	BLS	ALS	BLS	ALS
Transportation Destination Category	354421(2)	93583(1)		
No Transportation (0)	89309	12130	25	13
Hospital (1)	249219	78068	70	83
ER (2)	2830	609	1	1
Clinic (3)	1325	189	0	0
Other (4)	11738	2587	3	3
Transport Level	354526(2)	93608(1)		
No Transportation (0)	87174	12016	25	13
BLS (1)	203679	36444	57	39
ALS (2)	41919	42744	12	46
Other (3)	21654	2404	6	3
ActionTaken	292198(19)	85051(10)		
Exam Only (1)	14100	12582	15	15
Exam and Assist (2)	76705	71253	83	84
No Exam Needed (3)	192	138	0	0
Patient Refused Treatment (4)	892	817	1	1
Service Aid/Patient Assist (5)	244	195	0	0
Cancelled (6)	27	4	0	0
No Patient Found (7)	505	62	1	0
HighestLevelCareReceived	273305(24)	79011(16)		
First Responder (1)	6906	762	3	1
BLS (EMT) (2)	205636	17229	75	22
BLS (Intermediate) (3)	4352	0	2	0
ALS (Paramedic) (4)	53810	60816	20	77
No Training (N)	2	1	0	0
Other Health Care Provider (O)	2	0	0	0
*	2597	203	1	0

## APPENDIX 2:

### DATA CLEANING AND PREPARATION—R CODE

#### Restricting The Dataset To Non-Missing Age And Gender Data

##### AGE DATA

```
describe(emsBLS$PatientAgeYears)
BLS <- emsBLS
BLS$PatientAgeYears[is.na(BLS$PatientAgeYears)] <- -1
emsBLS <- subset(BLS, PatientAgeYears>=0)
describe(emsBLS)
describe(emsBLS$PatientAgeYears)
```

##### GENDER DATA

```
describe(emsBLS$PatientGenderID)
describe(BLS$PatientGenderID)

sum(is.na(emsBLS$PatientGenderID))
BLS$PatientGenderID[is.na(BLS$PatientGenderID)] <- 9
emsBLS <- subset(BLS, PatientAgeYears>=0 & PatientGenderID<3)
describe(emsBLS)
describe(emsBLS$PatientGenderID)
```

#### Demographic Variables: Age, Gender, And Time.

##### AGE DATA

```
emsBLS$age6cat <- NA
emsBLS$age6cat[PatientAgeYears>=0 & PatientAgeYears<5] <- "1)0to4"
emsBLS$age6cat[PatientAgeYears>4 & PatientAgeYears<15] <- "2)5to14"
emsBLS$age6cat[PatientAgeYears>14 & PatientAgeYears<45] <- "3)15to44"
emsBLS$age6cat[PatientAgeYears>44 & PatientAgeYears<65] <- "4)45to64"
emsBLS$age6cat[PatientAgeYears>64 & PatientAgeYears<85] <- "5)65to84"
emsBLS$age6cat[PatientAgeYears>84] <- "6)above85"

emsBLS$age3Cat <- NA
emsBLS$age3Cat[PatientAgeYears>=0 & PatientAgeYears<65] <- "below65"
emsBLS$age3Cat[PatientAgeYears>64 & PatientAgeYears<85] <- "65to84"
emsBLS$age3Cat[PatientAgeYears>84] <- "above85"
```

```
UPDATE ems_ExtremeHeatBLS SET agecat='1' where PatientAgeYears between 0 and 4;
UPDATE ems_ExtremeHeatBLS SET agecat='2' where PatientAgeYears between 5 and 14;
UPDATE ems_ExtremeHeatBLS SET agecat='3' where PatientAgeYears between 15 and 44;
UPDATE ems_ExtremeHeatBLS SET agecat='4' where PatientAgeYears between 45 and 64;
UPDATE ems_ExtremeHeatBLS SET agecat='5' where PatientAgeYears between 65 and 84;
UPDATE ems_ExtremeHeatBLS SET agecat='6' where PatientAgeYears>84;
select PatientAgeYears, agecat from ems_ExtremeHeatBLS;
```

## GENDER DATA

```
emsBLS$Gender <- NA
emsBLS$Gender[emsBLS$PatientGenderID==1] <- "Male"
emsBLS$Gender[emsBLS$PatientGenderID==2] <- "Female"
```

## TIME

```
emsBLS$Year = format(emsBLS$IncidentDate, "%Y")
emsBLS$Month = format(emsBLS$IncidentDate, "%M")
```

## Location Specific Variables: Property Use And Location Type

### PROPERTY USE

```
emsBLS$PropUseGrp <- emsBLS$PropertyUse
emsBLS$PropUseGrp <- as.character(emsBLS$PropUseGrp)
```

```
emsBLS$PropGroups <- NA
emsBLS$PropGroups[grep("[0NU]", c(emsBLS$PropUseGrp))] <- "Other"
emsBLS$PropGroups[grep("^1", c(emsBLS$PropUseGrp))] <- "Assembly"
emsBLS$PropGroups[grep("^2", c(emsBLS$PropUseGrp))] <- "Educational"
emsBLS$PropGroups[grep("^3", c(emsBLS$PropUseGrp))] <- "Health Care, Detention, &
Correction"
emsBLS$PropGroups[grep("^4", c(emsBLS$PropUseGrp))] <- "Residential"
emsBLS$PropGroups[grep("^5", c(emsBLS$PropUseGrp))] <- "Mercantile, Business, Other"
emsBLS$PropGroups[grep("^6", c(emsBLS$PropUseGrp))] <- "Industrial, Utility, Defense,
Agriculture, Mining"
emsBLS$PropGroups[grep("^7", c(emsBLS$PropUseGrp))] <- "Manufacturing, Processing"
emsBLS$PropGroups[grep("^8", c(emsBLS$PropUseGrp))] <- "Storage"
emsBLS$PropGroups[grep("^9", c(emsBLS$PropUseGrp))] <- "Outside or Special Property"
```

### LOCATION TYPE

```
emsBLS$Location <- NA
emsBLS$Location[LocationTypeID==1] <- "Residence"
emsBLS$Location[LocationTypeID==2] <- "Farm"
emsBLS$Location[LocationTypeID==3] <- "Mine/Quarry"
emsBLS$Location[LocationTypeID==4] <- "Industrial Place"
emsBLS$Location[LocationTypeID==5] <- "Recreation or Sport Facility"
emsBLS$Location[LocationTypeID==6] <- "Adult Family Home"
emsBLS$Location[LocationTypeID==7] <- "Nursing Home"
emsBLS$Location[LocationTypeID==8] <- "Medical Facility"
emsBLS$Location[LocationTypeID==9] <- "Street"
emsBLS$Location[LocationTypeID==10] <- "Highway"
emsBLS$Location[LocationTypeID==11] <- "Public Building"
emsBLS$Location[LocationTypeID==12] <- "Educational Institution"
emsBLS$Location[LocationTypeID==13] <- "Other Location"
emsBLS$Location[LocationTypeID==99] <- "Unknown"
```

**Health Outcome Variables: Idc, Patient Type, Procedure, Flow Chart, Transportation Destination, Transport Level, And Action Taken**  
INITIAL DISPATCH CODE (IDC)

```
emsBLS$IDCx <- emsBLS$InitialDispatchCode  
emsBLS$IDCx <- as.character(emsBLS$IDCx)
```

```
emsBLS$IDCsub <- gsub("[MPQRYT]", "_", c(emsBLS$IDCx), ignore.case=TRUE,  
perl=FALSE)
```

```
emsBLS$IDC <- NA  
emsBLS$IDC[grep("^1_", c(emsBLS$IDCsub), perl=FALSE)] <- "Abdominal/Back/Groin  
Pain"  
emsBLS$IDC[grep("^2_", c(emsBLS$IDCsub), perl=FALSE)] <- "Anaphylaxis/Allergic  
Reaction"  
emsBLS$IDC[grep("^3_", c(emsBLS$IDCsub), perl=FALSE)] <- "Infectious Disease"  
emsBLS$IDC[grep("^4_", c(emsBLS$IDCsub), perl=FALSE)] <- "Bleeding"  
emsBLS$IDC[grep("^5_", c(emsBLS$IDCsub), perl=FALSE)] <- "Breathing Difficulty"  
emsBLS$IDC[grep("^6_", c(emsBLS$IDCsub), perl=FALSE)] <- "Cardiac Arrest"  
emsBLS$IDC[grep("^7_", c(emsBLS$IDCsub), perl=FALSE)] <- "Chest Discomfort/Heart  
Problems"  
emsBLS$IDC[grep("^8_", c(emsBLS$IDCsub), perl=FALSE)] <- "Choking"  
emsBLS$IDC[grep("^9_", c(emsBLS$IDCsub), perl=FALSE)] <- "Diabetic"  
emsBLS$IDC[grep("^10_", c(emsBLS$IDCsub), perl=FALSE)] <- "Environmental/Toxic  
Exposure"  
emsBLS$IDC[grep("^11_", c(emsBLS$IDCsub), perl=FALSE)] <- "Medical Knowledge"  
emsBLS$IDC[grep("^12_", c(emsBLS$IDCsub), perl=FALSE)] <- "Head/Neck"  
emsBLS$IDC[grep("^13_", c(emsBLS$IDCsub), perl=FALSE)] <-  
"Mental/Emotional/Psychological"  
emsBLS$IDC[grep("^14_", c(emsBLS$IDCsub), perl=FALSE)] <- "O.D./Poisoning"  
emsBLS$IDC[grep("^15_", c(emsBLS$IDCsub), perl=FALSE)] <-  
"Pregnancy/Childbirth/GYN"  
emsBLS$IDC[grep("^16_", c(emsBLS$IDCsub), perl=FALSE)] <- "Seizures"  
emsBLS$IDC[grep("^17_", c(emsBLS$IDCsub), perl=FALSE)] <- "Sick(unknown)/Other"  
emsBLS$IDC[grep("^18_", c(emsBLS$IDCsub), perl=FALSE)] <- "Stroke(CVA)"  
emsBLS$IDC[grep("^19_", c(emsBLS$IDCsub), perl=FALSE)] <-  
"Unconscious/Unresponsive/Synope/Weak"  
emsBLS$IDC[grep("^20_", c(emsBLS$IDCsub), perl=FALSE)] <- "Pediatric Emergency"  
emsBLS$IDC[grep("^21_", c(emsBLS$IDCsub), perl=FALSE)] <- "Assault Trauma"  
emsBLS$IDC[grep("^22_", c(emsBLS$IDCsub), perl=FALSE)] <- "Burns-  
Thermal/Electric/Chemical"  
emsBLS$IDC[grep("^23_", c(emsBLS$IDCsub), perl=FALSE)] <- "Drowning/Near  
Drowning/Diving or Water-Related Injury"  
emsBLS$IDC[grep("^24_", c(emsBLS$IDCsub), perl=FALSE)] <- "Falls/Accidents/Pain"  
emsBLS$IDC[grep("^25_", c(emsBLS$IDCsub), perl=FALSE)] <- "Motor Vehicle Accident"
```

*(MVA)"*

```
emsBLS$IDC[grep("^(26_)", c(emsBLS$IDCsub), perl=FALSE)] <- "Animal Bites"
```

PATIENT TYPE

```
emsBLS$PtTypex <- emsBLS$PatientTypeCode
```

```
emsBLS$PtTypex <- as.character(emsBLS$PtTypex)
```

```
emsBLS$PtType <- NA
```

```
emsBLS$PtType[grep("(110)|(111)|(112)|(113)|(114)|(115)|(116)|(117)|(118)|(119)|(11N)|(11B)|  
|(11X)|(120)|(121)|(122)|(123)|(124)|(125)|(126)|(127)|(128)|(129)|(12N)|(12B)|(12X)|(1  
30)|(131)|(132)|(133)|(134)|(135)|(136)|(137)|(138)|(139)|(13N)|(13B)|(13X)|(140)|(141)  
|(142)|(143)|(144)|(145)|(146)|(147)|(148)|(149)|(14N)|(14B)|(14X)|(150)|(151)|(152)|(1  
53)|(154)|(155)|(156)|(157)|(158)|(159)|(15N)|(15B)|(15X)|(160)|(161)|(162)|(163)|(164)  
|(165)|(166)|(167)|(168)|(169)|(16X)|(170)|(171)|(172)|(173)|(174)|(175)|(176)|(177)|(17  
8)|(179)|(17X)|(180)|(181)|(182)|(183)|(184)|(185)|(186)|(187)|(188)|(189)|(18X)|(190)|(  
191)|(192)|(193)|(194)|(195)|(196)|(197)|(198)|(199)|(19X)|(1A0)|(1A1)|(1A2)|(1A3)|(1A  
4)|(1A5)|(1A8)|(1A9)|(1AB)|(1AN)|(1M0)|(1M1)|(1M2)|(1M3)|(1M4)|(1M5)|(1M6)|(1M7  
)|(1M8)|(1M9)|(1MB)|(1MN)|(1XX)", c(emsBLS$PtTypex), perl=FALSE)] <- "Trauma"
```

```
emsBLS$PtType[grep("(201)|(202)|(209)", c(emsBLS$PtTypex), perl=FALSE)] <-  
"Anaphylaxis/Allergy"
```

```
emsBLS$PtType[grep("(211)|(212)|(213)|(214)|(215)|(216)|(217)|(218)|(219)|(220)",  
c(emsBLS$PtTypex), perl=FALSE)] <- "Cardiovascular"
```

```
emsBLS$PtType[grep("(221)|(222)|(223)|(224)|(225)|(226)|(227)|(228)|(229)",  
c(emsBLS$PtTypex), perl=FALSE)] <- "Respiratory"
```

```
emsBLS$PtType[grep("(231)|(232)|(233)|(234)|(235)|(236)|(237)|(238)|(239)|(271)",  
c(emsBLS$PtTypex), perl=FALSE)] <- "Neurological"
```

```
emsBLS$PtType[grep("(241)|(242)|(243)|(244)|(249)", c(emsBLS$PtTypex), perl=FALSE)] <-  
"Abdominal/Genito-Urinary"
```

```
emsBLS$PtType[grep("(251)|(252)|(253)|(254)|(255)|(256)|(259)", c(emsBLS$PtTypex),  
perl=FALSE)] <- "Metabolic/Endocrine"
```

```
emsBLS$PtType[grep("(261)|(262)|(263)|(264)|(265)|(266)|(269)", c(emsBLS$PtTypex),  
perl=FALSE)] <- "Alcohol/Drug"
```

```
emsBLS$PtType[grep("(272)|(274)|(279)|(281)|(282)|(284)|(285)|(286)|(287)|(288)|(289)|(290)|  
(291)|(292)|(299)", c(emsBLS$PtTypex), perl=FALSE)] <- "Other Medical"
```

```
emsBLS$PtType[grep("(301)|(302)|(303)|(309)", c(emsBLS$PtTypex), perl=FALSE)] <-  
"OB/GYN"
```

```
emsBLS$PtType[grep("(401)|(402)|(403)|(404)|(409)", c(emsBLS$PtTypex), perl=FALSE)] <-  
"Psychological"
```

```
emsBLS$PtType[grep("(501)|(502)|(503)|(504)|(505)|(506)|(507)|(508)|(509)|(510)|(511)|(512)|  
(513)|(514)|(515)|(516)|(601)|(999)", c(emsBLS$PtTypex), perl=FALSE)] <- "Other-  
Non Diagnostic"
```

```
##Trauma
```

```
emsBLS$Trauma <- ifelse(emsBLS$PtType=="Trauma", 1, 0)
```

```
##Non-Trauma
```

```

emsBLS$NonTrauma <- ifelse((emsBLS$PtType!="Trauma" & emsBLS$PtType!="Other-Non
Diagnostic"), 1, 0)
##Anaphylaxis/Allergy
emsBLS$Allergy <- ifelse(emsBLS$PtType=="Anaphylaxis/Allergy", 1, 0)
##Cardiovascular
emsBLS$Cardio <- ifelse(emsBLS$PtType=="Cardiovascular", 1, 0)
##Respiratory
emsBLS$Resp= ifelse(emsBLS$PtType=="Respiratory", 1, 0)
###Asthma
emsBLS$Asthma <- ifelse(emsBLS$PtTypex==226, 1, 0)
###Emphysema/COPD
emsBLS$COPD <- ifelse(emsBLS$PtTypex==227, 1, 0)
##Neurological
emsBLS$Neuro <- ifelse(emsBLS$PtType=="Neurological", 1, 0)
###Suspected CVA
emsBLS$CVA <- ifelse(emsBLS$PtTypex==234, 1, 0)
###Suspected TIA
emsBLS$TIA <- ifelse(emsBLS$PtTypex==238, 1, 0)
##Abdominal/Genito-Urinary
emsBLS$Abdo <- ifelse(emsBLS$PtType=="Abdominal/Genito-Urinary", 1, 0)
##Metabolic/Endocrine
emsBLS$Metab <- ifelse(emsBLS$PtType=="Metabolic/Endocrine", 1, 0)
###Diabetese
emsBLS$Diabetes <-
ifelse((emsBLS$PtTypex==251|emsBLS$PtTypex==252|emsBLS$PtTypex==253|
emsBLS$PtTypex==254| emsBLS$PtTypex==255), 1, 0)
##Other Medical
emsBLS$Med <- ifelse(emsBLS$PtType=="Other Medical", 1, 0)
###Heat Illness and Dehydration (Exhaustion too?)
emsBLS$Heat <- ifelse((emsBLS$PtTypex==285|emsBLS$PtTypex==272), 1, 0)
##OB/GYN
emsBLS$OBGYN <- ifelse(emsBLS$PtType=="OB/GYN", 1, 0)
##Psychological
emsBLS$Psych <- ifelse(emsBLS$PtType=="Psychological", 1, 0)

```

#### PROCEDURE & FLOW CHART CODES

```

grep("^(Proc)", colnames(emsBLS))
emsBLS[, 20:60] <- lapply(emsBLS[,20:60], FUN=function(x) recode(x, "2=0"))
emsBLS$FC_DiastolicPalp <- recode(emsBLS$FC_DiastolicPalp, "2=0")

```

#### TRANSPORTATION DESTINATION, TRANSPORT LEVEL, & ACTION TAKEN

```

emsBLS$TransportDestinationCategory[emsBLS$TransportDestinationCategory== -1] <- NA
emsBLS$TransportLevel[emsBLS$TransportLevel== -1] <- NA
emsBLS$ActionTaken[emsBLS$ActionTaken== -1] <- NA

```

## APPENDIX 3:

### METHODS—RELATIVE RISK ANALYSIS

The following appendix describes the methods used to conduct the relative risk analysis from specific aim 1. This approach used Poisson regression to estimate the difference in expected EMS counts on heat days compared to non-heat days after accounting for variation within the population, thus allowing for comparison across different years. Methods and RStudio version 0.97.449 code were based on the work of Busch Isaksen et al. 2014. This appendix includes the threshold selection, relative risk analysis, and methods used to assess the potential effects of heat characteristics.

#### Tables

- 3.1—Mean and max Humidex by summer month for study period
- 3.2—Humidex percentiles and model fit

#### Threshold Selection

Extreme heat can be defined as a threshold temperature chosen *a priori* or as a percentile of previously recorded temperatures for the specific study region. Since the latter definition is generally preferred to allow for location specific variation of effects (EPA 2006), extreme heat was defined as the 90<sup>th</sup>, 95<sup>th</sup>, or 99<sup>th</sup> percentile of full year humidex values based on the best Akaike Information Criterion (AIC) for the maximum likelihood best fit of the data within the model [Jackson et al. 2010; Medina-Ramon. et al, 2006; Vaidyanathan 2013]. It should be noted that while the threshold selection incorporated full year humidex values, the analyses of an association between extreme heat and EMS calls only included warmer months (May 1<sup>st</sup> through September 30<sup>th</sup>).

To determine the threshold, the percentiles for daily maximum humidex over 12 months for the 6 year period were first calculated for 99<sup>th</sup>, 95<sup>th</sup>, 90<sup>th</sup>, 85<sup>th</sup>, and 50<sup>th</sup>. This was followed by aggregating of the EMS call data by date and then divided by the number of days in the study period to get daily call count averages. Since the study period only included the 153 days in the warmer months, the total number of days in the 6 year timeframe was 918. For the BLS data, the average number of calls per day was 393.7 and for the ALS data there was an average of 103 calls per day.

Next, the meteorological data was formatted into year, month, date, and summer variables, aggregated and summarized by month, abbreviated where necessary, and merged with the EMS data by date. Please see Table 3.1 for monthly humidex values averaged across the 6-year study timeframe. King County population data was also merged with the EMS data for inclusion in the models used for threshold selection. Background King County population data is sourced from Washington State’s Office of Financial Management [OFM 2012; OFM 2013] and was included to account for changes in population over the study timeframe. This data included counts for all ages as well as the six age groups defined in appendix 1.

Table 3.1: Mean and max humidex (°C) by summer month for entire study period (2007-2012).		
Month	Humidex °C	
	Mean	Max
May	15.65	36.08
June	19.3	37.75
July	26.94	44.74
August	25.54	41.42
Sept	21.91	34.78

The optimum threshold was selected based on the Akaike Information Criterion (AIC) for the maximum likelihood best fit of the data within the model. Days with average maximum humidex values at or above this threshold were defined as extreme heat days. For the BLS data,

the 95<sup>th</sup> percentile (29.7 °C) had the maximum likelihood of model fit, followed by 90<sup>th</sup> and 99<sup>th</sup>, but for the ALS data, the 99<sup>th</sup> percentile (36.7 °C) fit the data the best, followed by 95<sup>th</sup> and 90<sup>th</sup> percentiles. Please see table 3.2. For comparability with the ALS data as well as other recent work by Busch Isaksen et al. (2014), both the 95<sup>th</sup> and 99<sup>th</sup> percentiles are used for the BLS analyses, although the analysis using the 95<sup>th</sup> percentile should be considered primary.

	99th	95th	90th	50th
°C	36.72	29.72	26.26	11.56
°F	98.1	85.5	79.27	52.81
BLS AIC	1980.89	1964.78	1976.51	
ALS AIC	1406.38	1422.03	1425.98	

### Relative Risk Analysis

The relative risk analysis was conducted for both the BLS and ALS datasets for all causes, trauma, non-trauma, all patient type groups, as well as specific patient types (seizures, febrile seizures, diabetes, heat and dehydration, suspected CIA, suspected TIA, asthma, and emphysema/COPD), and level of transportation by all ages as well as the 6 age categories. The RR equation was as follows:

$$\log(\mu_j / population) = \beta_0 + \beta_1 I_j\{humidex > threshold\}$$

Where  $j$  indexed the day,  $\mu_j$  was the expected call count on day  $j$ , and  $I_j\{humidex > threshold\}$  was the indicator of a heat day, defined as whether its humidex exceeded a threshold.

In order to incorporate age groups, a matrix was created by age category and then expanded to include date and call counts. Using this matrix, individual variables were created for each cause of interest. A function was used to create final counts of causes of calls by date and age in the generalized linear model used in the relative risk analysis. Results were provided for the

relative risk (95% CIs), average calls per extreme heat or non-extreme heat day, and total calls for all extreme heat or non-extreme heat days.

### **Effects of Heat Characteristics**

Two characteristics of extreme heat were hypothesized to have the potential to increase or decrease the risk of an EMS call; the duration [Mastrangelo et al. 2007] of the extreme heat and the cooling down of temperatures at night [Schwartz 2005]. Heat duration was defined as a heat day's position in a consecutive series of heat days, the hypothesis being that as the heat increases in duration, the effects on health increase. The cool down effect was defined as the difference in high to low humidex on any day above the threshold. This effect was hypothesized to decrease the effects of extreme heat on health as the magnitude of cooling down increased. These characteristics were assessed for each data set on an all-ages, all-causes basis only using the statistical package "GAM" for RStudio version 0.97.449.

## APPENDIX 4:

### METHODS—RELATIVE RISK ANALYSIS—R CODE

#### Threshold Selection

```
qMaxHum99 = quantile(MetKingAvgEMS$AvCountyWideMaxHum, 0.99)
qMaxHum95 = quantile(MetKingAvgEMS$AvCountyWideMaxHum, 0.95)
qMaxHum90 = quantile(MetKingAvgEMS$AvCountyWideMaxHum, 0.90)
qMaxHum85 = quantile(MetKingAvgEMS$AvCountyWideMaxHum, 0.85)
qMaxHum50 = quantile(MetKingAvgEMS$AvCountyWideMaxHum, 0.50)
print(cbind(qMaxHum99, qMaxHum95, qMaxHum90, qMaxHum85, qMaxHum50))
```

```
emsBLS$count = 1
emsBLS$Date = emsBLS$IncidentDate
```

```
emsBLS.date= aggregate(count ~ Date,data=emsBLS ,FUN=sum)
dim(emsBLS.date)
nDays = 6*153
```

```
sum(emsBLS.date$count)/nDays
```

```
MetKingAvgEMS$Year = format(MetKingAvgEMS$metdate,"% Y")
MetKingAvgEMS$month = months(MetKingAvgEMS$metdate)
MetKingAvgEMS$Date = MetKingAvgEMS$metdate
MetKingAvgEMSSummer = MetKingAvgEMS[MetKingAvgEMS$month %in%
  c("May","June","July","August","September"),]
```

```
aggregate(MetKingAvgEMSSummer$AvCountyWideMaxHum,
  by=list(MetKingAvgEMSSummer$month), FUN=mean)
aggregate(MetKingAvgEMSSummer$AvCountyWideMaxHum,
  by=list(MetKingAvgEMSSummer$month), FUN=max)
```

```
quantile(MetKingAvgEMSSummer$AvCountyWideMaxHum, c(.50, .90, 0.95, .99))
```

```
tem = as.character(MetKingAvgEMSSummer$month)
tem2 = sapply(tem,substr,start=1,stop=3)
names(tem2)<-NULL
MetKingAvgEMSSummer$month = as.factor(tem2)
##adjust the order of factor variables
MetKingAvgEMSSummer$month <- factor(MetKingAvgEMSSummer$month, levels = c("May","Jun",
  "Jul", "Aug","Sep"))
```

```
emsBLS.date = merge(emsBLS.date, MetKingAvgEMSSummer , by="Date", all=T )
```

```
emsBLS.date$time <- c(1: nDays)
head(emsBLS.date)
emsBLS.date$Year <- as.numeric(format(as.Date(emsBLS.date$Date), format = "% Y"))
emsBLS.date$metdate <- NULL
```

```
popking=read.table(paste(DataPath, "kingpop2013.csv",sep=""),sep="!",header=T,
```

```

colClasses=c('character',rep('numeric',6)))

totalking = apply(popking[,2:7],MARGIN=2,sum) #or 3,7?
totalking = cbind(c(2007:2012), totalking)
rownames(totalking) <-NULL
colnames(totalking) <- c("Year", "Popu")

emsBLS.date=merge(emsBLS.date,totalking,by="Year",all=T)
emsBLS.date$logPopu = log(emsBLS.date$Popu)

emsBLS.date$humidex = emsBLS.date$AvCountyWideMaxHum
q0 = qnorm(0.975)

summary(emsBLS.date)

mod99 <-glm(count~offset(logPopu)+I((AvCountyWideMaxHum>qMaxHum99)*1),
  data=emsBLS.date,family = quasi(link=log,variance=mu))
mod95 <-glm(count~offset(logPopu)+I((AvCountyWideMaxHum>qMaxHum95)*1),
  data=emsBLS.date,family = quasi(link=log,variance=mu))
mod90 <-glm(count~offset(logPopu)+I((AvCountyWideMaxHum>qMaxHum90)*1),
  data=emsBLS.date,family = quasi(link=log,variance=mu))
c(mod90$deviance,mod95$deviance,mod99$deviance)
opt.RR = qMaxHum95

```

### Relative Risk Analysis

```

popuAgecat = matrix(0,6*6,3)
popuAgecat[,1] = rep(c(2007:2012),rep(6,6))
popuAgecat[,2] = rep(c(1:6),6)
tem = 1
for (i in 2007:2012){
  popuAgecat[tem:(tem+5),3]= popking[,paste("X",i,sep="")]
  tem = tem+5+1
}
colnames(popuAgecat) = c("Year", "agecat", "Popu")
popuAgecat = as.data.frame(popuAgecat)

popuAge3cat.popu = rep(0,3*6)
tem = 1
for (i in 2007:2012){
  temPopu = popking[,paste("X",i,sep="")]
  popuAge3cat.popu[tem:(tem+2)]= c(sum(temPopu[1:4]),temPopu[5],temPopu[6])
  tem = tem+2+1
}
popuAge3cat = data.frame(Year = rep(c(2007:2012),rep(3,6)),
age3Cat=rep(c("below64", "65to84", "above85"),6),Popu=popuAge3cat.popu)

agg.date.agecat <- function(idctCause){
  temDat = aggregate(count~Date + agecat,data=emsBLS[idctCause,], FUN=sum)
  dat.cause = merge(expGrid.date.agecat, temDat,by=c('Date','agecat'),all=T)
  dat.cause$count[is.na(dat.cause$count)]=0
  dat.cause$logPopu = log(dat.cause$Popu)
}

```

```

dat.cause$HD = (dat.cause$humidex>qMaxHum95)*1
ret = dat.cause
}

opt.RR = qMaxHum95
expGrid.date.agecat = expand.grid(emsBLS.date$Date,c(1:6))
colnames(expGrid.date.agecat ) = c('Date','agecat')

expGrid.date.agecat = merge(expGrid.date.agecat ,
emsBLS.date[,c('humidex','Date','time','month','Year')],by='Date')
expGrid.date.agecat = merge(expGrid.date.agecat , popuAgecat, by=c('Year','agecat'))

dat.allCauses.agecat = agg.date.agecat(idctCause= rep(1==1,dim(emsBLS)[1]))

dat.nontraumatic.agecat = agg.date.agecat(emsBLS$NonTraumatic==1)
dat.resp.agecat = agg.date.agecat(emsBLS$Resp==1)
dat.trauma.agecat = agg.date.agecat(emsBLS$Trauma==1)
dat.cardio.agecat = agg.date.agecat(emsBLS$Cardio==1)
dat.allergy.agecat = agg.date.agecat (emsBLS$Allergy==1)
dat.CVA.agecat = agg.date.agecat (emsBLS$CVA==1)
dat.TIA.agecat = agg.date.agecat (emsBLS$TIA==1)
dat.heat.agecat = agg.date.agecat (emsBLS$Heat==1)
dat.diabetes.agecat = agg.date.agecat (emsBLS$Diabetes==1)
dat.copd.agecat = agg.date.agecat (emsBLS$COPD==1)
dat.asthma.agecat = agg.date.agecat (emsBLS$Asthma==1)
dat.neuro.agecat = agg.date.agecat (emsBLS$Neuro==1)
dat.abdo.agecat = agg.date.agecat (emsBLS$Abdo==1)
dat.metab.agecat = agg.date.agecat (emsBLS$Metab==1)
dat.med.agecat = agg.date.agecat (emsBLS$Med==1)
dat.drug.agecat = agg.date.agecat (emsBLS$Drug==1)
dat.obgyn.agecat = agg.date.agecat (emsBLS$OBGYN==1)
dat.psych.agecat = agg.date.agecat (emsBLS$Psych==1)
dat.seizure.agecat = agg.date.agecat (emsBLS$Seizure==1)
dat.febrileseizure.agecat = agg.date.agecat (emsBLS$FebSeiz==1)
dat.notrans.agecat = agg.date.agecat (emsBLS$NoTrans==1)
dat.BLStrans.agecat = agg.date.agecat (emsBLS$BLStrans==1)
dat.ALStrans.agecat = agg.date.agecat (emsBLS$ALStrans==1)
dat.othertrans.agecat = agg.date.agecat (emsBLS$OtherTrans==1)

agg.date <- function(idctCause){
temDat= aggregate(count~Date ,data=emsBLS[idctCause,], FUN=sum)
dat.cause = merge(expGrid.date, temDat, by=c('Date'),all=T)
dat.cause$count[is.na(dat.cause$count)]=0
dat.cause$logPopu = log(dat.cause$Popu)
dat.cause$HD = (dat.cause$humidex>qMaxHum95)*1
ret = dat.cause
}

expGrid.date = expand.grid(emsBLS.date$Date)
colnames(expGrid.date ) = c('Date')

```

```
expGrid.date = merge(expGrid.date, emsBLS.date[,c('humidex','Date','time','month','Year')],by='Date')
expGrid.date = merge(expGrid.date, totalking, by='Year')
```

```
dat.allCauses = agg.date(rep(1==1,dim(emsBLS)[1]))
```

```
dat.nontraumatic= agg.date(emsBLS$NonTraumatic==1)
dat.resp = agg.date(emsBLS$Resp==1)
dat.trauma = agg.date(emsBLS$Trauma==1)
dat.cardio = agg.date(emsBLS$Cardio==1)
dat.allergy = agg.date(emsBLS$Allergy==1)
dat.CVA = agg.date(emsBLS$CVA==1)
dat.TIA = agg.date(emsBLS$TIA==1)
dat.heat = agg.date(emsBLS$Heat==1)
dat.diabetes = agg.date(emsBLS$Diabetes==1)
dat.copd = agg.date(emsBLS$COPD==1)
dat.asthma = agg.date(emsBLS$Asthma==1)
dat.neuro = agg.date(emsBLS$Neuro==1)
dat.abdo = agg.date(emsBLS$Abdo==1)
dat.metab = agg.date(emsBLS$Metab==1)
dat.med = agg.date(emsBLS$Med==1)
dat.drug = agg.date(emsBLS$Drug==1)
dat.obgyn = agg.date(emsBLS$OBGYN==1)
dat.psych = agg.date(emsBLS$Psych==1)
dat.seizure = agg.date(emsBLS$Seizure==1)
dat.febrileseizure = agg.date(emsBLS$FebSeiz==1)
dat.notrans = agg.date(emsBLS$NoTrans==1)
dat.BLStrans = agg.date(emsBLS$BLStrans==1)
dat.ALStrans = agg.date(emsBLS$ALStrans==1)
dat.othertrans = agg.date(emsBLS$OtherTrans==1)
```

```
nCause = 24
```

```
nAgeGroup = 6
```

```
q0 = qnorm(0.975)
```

```
allAgesResult = matrix(0,nCause+1 ,nAgeGroup+1)
```

```
rownames(allAgesResult) = c("allCauses", "nontraumatic", "resp", "trauma", "cardio", "allergy", "CVA",
" TIA", "heat", "diabetes", "COPD", "asthma", "neuro", "abdo", "metab", "med", "drug", "obgyn",
"psych", "seizure", "febrile seizure", "notrans", "BLStrans", "ALStrans", "othertrans")
colnames(allAgesResult) = c("allAges", "0-4", "5-14", "15-44", "45-64", "65-84", "85+")
```

```
numObs.table = numCallsPerDay.table = allAgesResult
```

```
for (j in 1:(1+nAgeGroup)){
  for (i in 1:(nCause+1)){
    if (j==1){
      if (i==1) dat.tem = emsBLS.date
      if (i==2) dat.tem = dat.nontraumatic
      if (i==3) dat.tem = dat.resp
      if (i==4) dat.tem = dat.trauma
      if (i==5) dat.tem = dat.cardio
      if (i==6) dat.tem = dat.allergy
      if (i==7) dat.tem = dat.CVA
```

```

if (i==8) dat.tem = dat.TIA
if (i==9) dat.tem = dat.heat
if (i==10) dat.tem = dat.diabetes
if (i==11) dat.tem = dat.copd
if (i==12) dat.tem = dat.asthma
if (i==13) dat.tem = dat.neuro
if (i==14) dat.tem = dat.abdo
if (i==15) dat.tem = dat.metab
if (i==16) dat.tem = dat.med
if (i==17) dat.tem = dat.drug
if (i==18) dat.tem = dat.obgyn
if (i==19) dat.tem = dat.psych
if (i==20) dat.tem = dat.seizure
if (i==21) dat.tem = dat.febrileseizure
if (i==22) dat.tem = dat.notrans
if (i==23) dat.tem = dat.BLStrans
if (i==24) dat.tem = dat.ALStrans
if (i==25) dat.tem = dat.othertrans
idctAgecat = rep(TRUE, dim(dat.tem)[1])
} else {
if (i==1) dat.tem = dat.allCauses.agecat
if (i==2) dat.tem = dat.nontraumatic.agecat
if (i==3) dat.tem = dat.resp.agecat
if (i==4) dat.tem = dat.trauma.agecat
if (i==5) dat.tem = dat.cardio.agecat
if (i==6) dat.tem = dat.allergy.agecat
if (i==7) dat.tem = dat.CVA.agecat
if (i==8) dat.tem = dat.TIA.agecat
if (i==9) dat.tem = dat.heat.agecat
if (i==10) dat.tem = dat.diabetes.agecat
if (i==11) dat.tem = dat.copd.agecat
if (i==12) dat.tem = dat.asthma.agecat
if (i==13) dat.tem = dat.neuro.agecat
if (i==14) dat.tem = dat.abdo.agecat
if (i==15) dat.tem = dat.metab.agecat
if (i==16) dat.tem = dat.med.agecat
if (i==17) dat.tem = dat.drug.agecat
if (i==18) dat.tem = dat.obgyn.agecat
if (i==19) dat.tem = dat.psych.agecat
if (i==20) dat.tem = dat.seizure.agecat
if (i==21) dat.tem = dat.febrileseizure.agecat
if (i==22) dat.tem = dat.notrans.agecat
if (i==23) dat.tem = dat.BLStrans.agecat
if (i==24) dat.tem = dat.ALStrans.agecat
if (i==25) dat.tem = dat.othertrans.agecat
idctAgecat = (dat.tem$agecat==j-1)
}
mod <- glm(count ~ offset(logPopu)+ HD, data = dat.tem[idctAgecat,],
           family = quasi(link=log,variance=mu))
betas = mod$coefficients
RR = exp(betas[-1])

```

```

seBetas = summary.glm( mod)$coefficients[,2]
RR_95CIu = exp(betas[-1]+q0*seBetas[-1])
RR_95CII = exp(betas[-1]-q0*seBetas[-1])
if (RR_95CII>1) starID = "*" else starID = ""
allAgesResult[i,j] =paste(round(RR[1],2), " (", round(RR_95CII[1],2), ",
",round(RR_95CIu[1],2),starID,sep="")
aveDailyCalls =
signif(tapply(dat.tem$count[idctAgecat],INDEX=dat.tem$HD[idctAgecat],FUN=mean),3)
totalCalls = tapply(dat.tem$count[idctAgecat],INDEX=dat.tem$HD[idctAgecat],FUN=sum)
numCallsPerDay.table[i,j] = paste("[",aveDailyCalls[1],', ',aveDailyCalls[2] , "]" ,sep="")
numObs.table[i,j] = paste("[",totalCalls[1],', ',totalCalls[2] , "]" ,sep="")
}
}

allAgesResult
numCallsPerDay.table
numObs.table

```

## Effects of Heat Characteristics

### ## Cool down effect ##

```

idct = emsBLS.date$humidex>opt.RR
library(gam)
emsBLS.date$cooldown = NA
emsBLS.date$cooldown = (emsBLS.date$humidex>=opt.RR)*1*(emsBLS.date$humidex-
emsBLS.date$AvCountyWidehmdxmin)
Mod.cool <- gam(count ~ cooldown + offset( logPopu ),family = quasi(link=log,variance=mu),
data=emsBLS.date[idct,] )
summary.glm(Mod.cool)
Mod2.cool <- glm(count ~ I(pmax(0,humidex-opt.RR)) + cooldown + offset( logPopu ),family =
quasi(link=log,variance=mu), data=emsBLS.date[idct,] )
summary.glm(Mod2.cool)

```

### ## Duration effect ##

```

emsBLS.date$abovethreshold = pmax(0,emsBLS.date$humidex-opt.RR)
emsBLS.date$HD = (emsBLS.date$humidex>opt.RR)*1
emsBLS.date$duration[1] = tem = emsBLS.date$HD[1]
for (i in 2:nDays){
if (emsBLS.date$HD[i] == 0) emsBLS.date$duration[i]= tem = 0 else emsBLS.date$duration[i] = tem
=tem+1
}
Mod.dur <- glm(count ~ duration + offset( logPopu ),family =
quasi(link=log,variance=mu),data=emsBLS.date[idct,] )
summary.glm(Mod.dur)
Mod2.dur <- glm(count ~ I(pmax(0,humidex-opt.RR)) + duration + offset( logPopu ),family =
quasi(link=log,variance=mu), data=emsBLS.date[idct,] )
summary.glm(Mod2.dur)

```

## APPENDIX 5:

### METHODS—TIME-SERIES ANALYSIS

The following appendix describes the methods used to conduct the time series analysis from specific aim 2. This approach models the relationship between daily Humidex values and EMS call rates. Methods and RStudio version 0.97.449 code was based on the work of Busch Isaksen et al. 2014. This appendix includes the time series analysis, assessment of potential effects modifiers, and assessment of heat characteristics.

#### Time Series Analysis

The time series used a nonparametric splining model with a piecewise linear fit with two knots. The first knot was set at the 50<sup>th</sup> percentile and the second, “optimum alert threshold”, was set based on exploration of the data in 0.1 degree increments between 25°C and 44.7°C Humidex. The time series equation was as follows:

$$Y_j \sim \text{Poisson}(P_j \mu_j), \text{ with}$$

$$\log(\mu_j) = \beta_0 + \beta_1(h_j - h_{q50})_+ + \beta_2(h_j - \hat{h}_0)_+ + s(t_j) + \sum_{l=6}^9 \beta_l I_{\{month=j-l\}}$$

Where  $Y_j$  as the observed EMS call count on day  $j$ ,  $P_j$  was the population on day  $j$ ,  $h_j$  was the county-wide average daily maximum humidex value on day  $j$ ,  $h_{q50}$  was the 50<sup>th</sup> percentile of Humidex from January 2007 to December 2012,  $h_0$  was the optimal alert threshold,  $s(t_j)$  was the natural cubic spline modeling the overall trend of calls over 6 years,  $(\beta_i$ 's) was a fixed effects adjustment for seasonal monthly effects,  $s(t_j)$  was the natural cubic spline modeling the overall trend of EMS calls over 6 years, and  $I_{\text{month}}$  was the indicator variable for months May through September.

Selection of the optimum alert threshold was based on the Akaike Information Criterion (AIC) for the maximum likelihood best fit of the model. However, prior to selecting the optimum threshold, the best model for the data needed to be determined. Four models were considered for this analysis. Each model was similar, with differences resulting from the inclusion or exclusion of variables describing values below or above the 50<sup>th</sup> percentile and below or above the threshold used in the relative risk analysis (95<sup>th</sup> or 99<sup>th</sup> percentile). These models required RStudio statistical packages “MGCV” and “GAM” as well as the calculation of the appropriate internal knots for select variables that require inclusion of degrees of freedom in the later uses of the model. Based on research by the CDC, the first internal knot used in the models was set at 47 based on the product of 7.7 and the number of years in the study period. The second internal knot was set at 5. Once the model had been selected (model 3 for both BLS and ALS data), the model was used to tune the threshold using the “GAM” statistical package.

Once the optimal threshold was determined, the optimal model was set and call count data was merged into the matrix. Estimates of percent increases in daily EMS calls associated with one degree increase above the optimum threshold were calculated using an intensity function in RStudio 0.97.449. Estimates by age group were calculated in a similar fashion after age categories are merged with the matrix.

### **Effect Modification and Effects of Heat Characteristics**

Due to constraints of the EMS data, the analysis of effect modification was restricted to gender. This variable was incorporated into the analysis as a covariate. Two characteristics of extreme heat were hypothesized to have the potential to increasing or decreasing the number of EMS call; the duration of the extreme heat and the cooling down of temperatures at night, respectively. To

assess the impacts of these characteristics, models were re-run with the inclusions of an additional variable for either duration or cool down.

## APPENDIX 6:

### METHODS—TIME-SERIES ANALYSIS—R CODE

#### Time Series Analysis

```
library("mgcv")
gam.explore <- gam(count ~ s(time,bs="cr",k=47) + s(humidex,bs="cr",k=5) + month + offset(logPopu
),
      method="GCV.Cp",family = quasi(link=log,variance=mu),data=emsBLS.date)
```

#### ## Piecewise TS model ##

```
qHum50summer = as.numeric(quantile(emsBLS.date$humidex,0.5) )
TSdat = emsBLS.date
thres =qMaxHum95
TSdat$belowQ50 = pmin(0,(TSdat$humidex-qHum50summer))
TSdat$belowThres = pmin(0,(TSdat$humidex-thres))
TSdat$aboveQ50 = pmax(0,(TSdat$humidex-qHum50summer))
TSdat$aboveThres = pmax(0,(TSdat$humidex-thres))
sum(TSdat$humidex>qMaxHum95)
TSdat$humidex = TSdat$humidex
TSdat$minHumidex = TSdat$countyHumidexMin
```

```
logN = log(918)
get.aicbic <- function(modTem,optDF=0){
  df = length(modTem$coefficients)-1 + optDF
  ret = c(modTem$deviance+2*df,modTem$deviance+logN*df)
}
```

```
get.mgcv <-function(modTStem){
  betas = summary(modTStem)$p.table[,1]
  PerctgChangeM = exp(betas[-1])-1
  seBetas = summary(modTStem)$p.table[,2]
  RR_95CIu = exp(betas[-1]+q0*seBetas[-1])-1
  RR_95CII = exp(betas[-1]-q0*seBetas[-1])-1
  TSResult = matrix(0,length(betas)-1,1)
  for (k in 1:(length(betas)-1)){
    TSResult[k,1] = paste(round(PerctgChangeM[k]*100,2), " (",
round(RR_95CII[k]*100,2),round(RR_95CIu[k]*100,2),") ")
  }
  rownames(TSResult)=names(betas)[-1]
  print(round(summary(modTStem)$p.table,digits=6))
  TSResult
}
```

#### ## mgcv Model 1 ##

```
mgcvMod1 <- gam(count~ s(time,bs="cr",k=47) + month+ belowQ50 +aboveThres + offset(logPopu),
      method="GCV.Cp",family = quasi(link=log,variance=mu),data=TSdat )
summary(mgcvMod1)
par(mfrow=c(1,1))
plot(mgcvMod1)
```

```

get.mgcv(mgcvMod1)

## mgcv Model 2 ##
mgcvMod2 <- gam(count ~ s(time,bs="cr",k=47) + month+ aboveQ50 +aboveThres + offset( logPopu ),
  method="GCV.Cp",family = quasi(link=log,variance=mu),data=TSdat )
summary(mgcvMod2 )
par(mfrow=c(1,1))
plot(mgcvMod2 )
get.mgcv(mgcvMod2 )

## mgcv Model 3 ##
mgcvMod3 <- gam(count~ s(time,bs="cr",k=47) + month + s(belowThres,bs="cr",k=5)+ aboveThres +
  offset( logPopu ) , method="GCV.Cp", family = quasi(link=log,variance=mu),data=TSdat )
summary(mgcvMod3 )
par(mfrow=c(1,2))
plot(mgcvMod3)
get.mgcv(mgcvMod3)
mgcvMod3$gcv.ubre*nDays
totalDf = sum(mgcvMod3$edf)
mgcvMod3$deviance+2*totalDf

## mgcv Model 4 ##
mgcvMod4 <- gam(count~ s(time,bs="cr",k=47) + month + belowQ50 + aboveQ50+ aboveThres +
  offset(logPopu), method="GCV.Cp",family = quasi(link=log,variance=mu),data=TSdat )
summary(mgcvMod4 )
par(mfrow=c(1,1))
plot(mgcvMod4)
get.mgcv(mgcvMod4)

#Function for get.aicbic.mgcv
get.aicbic.mgcv<- function(modTem){
  df = sum(modTem$edf)
  res = c(modTem$deviance+2*df,modTem$deviance+log(nDays)*df, round(df))
  names(res) = c('AIC','BIC','edf');      print(res)
  ret = res
}

### AIC BIC for four models ###
aicbicMat.form = matrix(0,4,3)
colnames(aicbicMat.form ) = c('AIC','BIC', 'edf' )
aicbicMat.form[1,] = get.aicbic.mgcv(mgcvMod1)
aicbicMat.form[2,] = get.aicbic.mgcv(mgcvMod2)
aicbicMat.form[3,] = get.aicbic.mgcv(mgcvMod3)
aicbicMat.form[4,] = get.aicbic.mgcv(mgcvMod4)
print(aicbicMat.form,digits=5)

## Tune the threshold (gam) ##
library(gam)

#Function logN
logN = log(918)

```

```

get.aicbic <- function(modTem,optDF=0){
  df = length(modTem$coefficients)-1 + optDF
  ret = c(modTem$deviance+2*df,modTem$deviance+logN*df)
}

#Function get.aicbic.gam
get.aicbic.gam = function(gam.tem){
  df = (gam.tem$df.null-gam.tem$df.residual)
  a = gam.tem$deviance+2*df
  b = gam.tem$deviance+logN*df
  res = c(a,b)
  names(res) = c('AIC','BIC'); print(res)
  ret=res
}

get.intensity = function(gamMod,thres,numTerms){
  betas = gamMod$coefficients
  if (numTerms==2){
    covMat = vcov(gamMod)[c('aboveQ50','aboveThres'),c('aboveQ50','aboveThres')]
    se.intensity = sqrt(c(1,1)%*%covMat%*%c(1,1))
    beta.intensity = sum(betas[c('aboveQ50','aboveThres')])
  } else if (numTerms==1){
    covMat = vcov(gamMod)['aboveThres','aboveThres']
    se.intensity = sqrt(covMat)
    beta.intensity = betas['aboveThres']
  }
  CIu = exp(beta.intensity+q0*se.intensity)-1
  CII = exp(beta.intensity-q0*se.intensity)-1
  rate = exp(beta.intensity)-1
  cat('One degree increase above',thres,'is associated with',round(rate*100,2),
    '% (', round(CII*100,2), '% ',round(CIu*100,2), '% )','increase in daily EMS calls','\n')
  ret=c(round(rate*100,2),round(CII*100,2),round(CIu*100,2) )
}

q0 = qnorm(0.975)

qHum50summer = as.numeric(quantile(emsBLS.date$humidex,0.5) )
TSdat = emsBLS.date
thres=qMaxHum95
TSdat$belowQ50 = pmin(0,(TSdat$humidex-qHum50summer))
TSdat$belowThres = pmin(0,(TSdat$humidex-thres))
TSdat$aboveQ50 = pmax(0,(TSdat$humidex-qHum50summer))
TSdat$aboveThres = pmax(0,(TSdat$humidex-thres))
sum(TSdat$humidex>thres) #110
TSdat$humidex = TSdat$humidex
TSdat$minHumidex = TSdat$countyHumidexMin

thresV = seq(25,44.7,0.1)

##Model 3
detach("package:mgcv")

```

```

library(gam)
aicbicMat = matrix(0,length(thresV),6)
colnames(aicbicMat) = c('Threshold_humidex','AIC','BIC','slope','slope_lower','slope_upper')
for (i in 1:length(thresV)){
  thresTem = aicbicMat[i,1] = thresV[i]
  TSdat$belowThres = pmin(0,TSdat$humidex-thresTem)
  TSdat$aboveThres = pmax(0,TSdat$humidex-thresTem)
  gam.tem <- gam(count~ s(time,df=4) + month + s(belowThres,df=1)+ aboveThres + offset( logPopu ),
    family = quasi(link=log,variance=mu), data=TSdat )
  aicbicMat[i,2:3] = get.aicbic.gam(gam.tem)
  aicbicMat[i,4:6] = get.intensity(gam.tem,thresTem,1)
  cat(i,'finished','cutoff',aicbicMat[i,1],'aic bic',aicbicMat[i,2:3],'\n')
}
id=which.min(aicbicMat[,2])
which.min(aicbicMat[,3])
aicbicMat[id,]

```

### ## The optimal TS model (gam)

```

library(gam)
opt.thres = 40.7
TSdat$aboveThres = pmax(0,(TSdat$humidex-opt.thres))
sum(TSdat$humidex>opt.thres) #4

```

```

gamMod.opt <- gam(count~ s(time,df=4) +month + s(belowThres,df=1)+ aboveThres + offset( logPopu
), family = quasi(link=log,variance=mu), data=TSdat )
summary.glm(gamMod.opt)
print(get.aicbic.gam(gamMod.opt))
get.intensity(gamMod.opt,opt.thres,1)

```

### ### optimal model for diff causes of Calls

```

agg.date.agecat <- function(idctCause){temDat = aggregate(count~Date +
  agecat,data=emsBLS[idctCause,], FUN=sum)
  dat.cause = merge(expGrid.date.agecat,temDat,by=c('Date', 'agecat'), all=T)
  dat.cause$count[is.na(dat.cause$count)]=0
  dat.cause$logPopu = log(dat.cause$Popu)
  ret = dat.cause
}
agg.date <- function(idctCause){
  temDat= aggregate(count~Date ,data=emsBLS[idctCause,], FUN=sum)
  dat.cause = merge(expGrid.date, temDat, by=c('Date'),all=T)
  dat.cause$count[is.na(dat.cause$count)]=0
  dat.cause$logPopu = log(dat.cause$Popu)
  ret = dat.cause
}
get.intensity = function(gamMod,thres,numTerms){
  betas = gamMod$coefficients
  if (numTerms==2){
    covMat = vcov(gamMod)[c('aboveQ50','aboveThres'),c('aboveQ50', 'aboveThres')]
    se.intensity = sqrt(c(1,1)%*%covMat%*%c(1,1))
    beta.intensity = sum(betas[c('aboveQ50','aboveThres')])
  } else if (numTerms==1){

```

```

covMat = vcov(gamMod)['aboveThres','aboveThres']
se.intensity = sqrt(covMat)
beta.intensity = betas['aboveThres']
}
CIu = exp(beta.intensity+q0*se.intensity)-1
CII = exp(beta.intensity-q0*se.intensity)-1
rate = exp(beta.intensity)-1
cat('One degree increase above',thres,'is associated with', round(rate*100,2),'% (', round(CII*100,2),'%
    ',round(CIu*100,2),'% )','increase in daily EMS Calls','\n' )
ret=c(round(rate*100,2),round(CII*100,2),round(CIu*100,2) )
}

qHum50summer = as.numeric(quantile(emsBLS.date$humidex,0.5) )

opt.thres=40.7
TSmod.opt.cause <-function(TSdat.cause){
  TSdat.cause$aboveQ50 = pmax(0,(TSdat.cause$humidex-qHum50summer))
  TSdat.cause$belowQ50 = pmin(0,(TSdat.cause$humidex-qHum50summer))
  TSdat.cause$belowThres = pmin(0,(TSdat.cause$humidex-opt.thres))
  TSdat.cause$aboveThres = pmax(0,(TSdat.cause$humidex-opt.thres))
  gamMod.opt.cause <- gam(count~ s(time,df=4) + month + s(belowThres,df=1)+ aboveThres + offset(
logPopu ), family = quasi(link=log,variance=mu),data=TSdat.cause )
  get.intensity(gamMod.opt.cause,opt.thres,1)
}

get.intensity(gamMod.opt,opt.thres,1)
TSmod.opt.cause(dat.nontraumatic)
TSmod.opt.cause(dat.resp)
TSmod.opt.cause(dat.trauma)
TSmod.opt.cause(dat.cardio)
TSmod.opt.cause(dat.allergy)
TSmod.opt.cause(dat.CVA)
TSmod.opt.cause(dat.TIA)
TSmod.opt.cause(dat.heat)
TSmod.opt.cause(dat.diabetes)
TSmod.opt.cause(dat.copd)
TSmod.opt.cause(dat.asthma)
TSmod.opt.cause(dat.neuro)
TSmod.opt.cause(dat.abdo)
TSmod.opt.cause(dat.metab)
TSmod.opt.cause(dat.med)
TSmod.opt.cause(dat.drug)
TSmod.opt.cause(dat.obgyn)
TSmod.opt.cause(dat.psych)
TSmod.opt.cause(dat.seizure)
TSmod.opt.cause(dat.febrileseizure)
TSmod.opt.cause(dat.notrans)
TSmod.opt.cause(dat.BLStrans)
TSmod.opt.cause(dat.ALStrans)
TSmod.opt.cause(dat.othertrans)

```

```
## Covariates ###
```

```
source(paste(CodePath, "functions.R", sep=""))
```

```
qHum50summer = as.numeric(quantile(emsBLS.date$humidex,0.5) )
```

```
opt.thres=40.7
```

```
TS3agecat.cause <- function(datTem, popuIn, popuName, allDataId=0){
  dat.covTem = aggregate(count ~Date + age3Cat,data=datTem,FUN=sum)
  expGrid = expand.grid(TSdat$Date,c("below64","65to84","above85"))
  colnames(expGrid) = c('Date','age3Cat')
  expGrid = merge(expGrid, TSdat[,c('humidex','Date','time','month','Year')],by='Date')
  expGrid = merge(expGrid, popuIn, by=c('Year',popuName))
  expGrid$aboveQ50 = pmax(0, expGrid$humidex - qHum50summer )
  expGrid$belowQ50 = pmin(0, expGrid$humidex - qHum50summer )
  expGrid$aboveThres = pmax(0, expGrid$humidex - opt.thres )
  expGrid$belowThres = pmin(0, expGrid$humidex - opt.thres )
  dat.cov = merge(expGrid,dat.covTem,by=c('Date','age3Cat'),all=T)
  dat.cov$count[is.na(dat.cov$count)]=0
  dat.cov$logPopu = log(dat.cov$Popu)
  gamMod.age3Cat <- gam(count~ age3Cat+aboveThres*age3Cat + s(belowThres,df=1)*age3Cat +
    s(time,df=4) + month + offset( logPopu ), family =
    quasi(link=log,variance=mu),data=dat.cov )
  summary.glm(gamMod.age3Cat)
  if (allDataId==1) {
    countByAge3Cat = tapply(emsBLS$count, emsBLS$age3Cat,sum)
    popuByAge3Cat = tapply(popuAge3cat$Popu,popuAge3cat$age3Cat,sum)
    callRateByAge3Cat =countByAge3Cat/ popuByAge3Cat
    print(rbind(countByAge3Cat,popuByAge3Cat,callRateByAge3Cat))
  }
  countByAge3Cat = tapply(datTem$count, datTem$age3Cat,sum); print("3")
  popuByAge3Cat = tapply(popuAge3cat$Popu,popuAge3cat$age3Cat,sum); print("4")
  callRateByAge3Cat =countByAge3Cat/ popuByAge3Cat
  tem = rbind(as.integer(countByAge3Cat),as.integer(popuByAge3Cat), round(callRateByAge3Cat,4))
  tem2 = tem[,c(3,1,2)]
  rownames(tem2) = c("calls","populations","CallRate")
  print(tem2)
  ret = rep(0,3)
  covLevels = c("below64","65to84","above85")
  nLevels = length(covLevels)
  tem = tapply(datTem$count, datTem[,popuName],sum, na.rm=T)
  tem = tem[!is.na(tem)]
  tem2 = tem[c(3,1,2)]
  tem2 = tem2/sum(tem2)
  cat("Proportion in the total calls","\n")
  print(tem2)
  cat("For ", covLevels[1], "\n")
  variables = c('aboveThres')
  ret[1] = get.intensity.TSage(gamMod.age3Cat, opt.thres ,variables)
  cat("For ", covLevels[2], "\n")
  variables = c('aboveThres','age3Cat65to84:aboveThres')
  ret[2] = get.intensity.TSage(gamMod.age3Cat, opt.thres ,variables)
```

```

cat("For ", covLevels[3], "\n")
variables = c('aboveThres','age3Catabove85:aboveThres')
ret[3] = get.intensity.TSage(gamMod.age3Cat,opt.thres,variables)
variables = c('age3Cat65to84:aboveThres')
cat("For ", covLevels[2],'compared to', covLevels[1],"\n")
get.intensity.TSage(gamMod.age3Cat,opt.thres,variables)
variables = c('age3Catabove85:aboveThres')
cat("For ", covLevels[3],'compared to', covLevels[1],"\n")
get.intensity.TSage(gamMod.age3Cat,opt.thres,variables)
ret
}

get.intensity.TSage <- function(gamMod, thres,variables){
  betas = gamMod$coefficients
  covMat = vcov(gamMod)[variables, variables]
  se.intensity = sqrt(rep(1,length(variables))%*%covMat%*%rep(1, length(variables)))
  beta.intensity = sum(betas[variables] )
  CIu = exp(beta.intensity+q0*se.intensity)-1
  CII = exp(beta.intensity-q0*se.intensity)-1
  if (CII>0) sigID='%* ' else sigID='%)'
  rate = exp(beta.intensity)-1
  cat('One degree increase above ',thres,' is associated with ',round(rate*100,2),'% (',
      round(CII*100,2),'% ',round(CIu*100,2), sigID, 'increase in daily EMS calls',\n',sep="" )
  ret = paste(round(rate*100,2),'% (', round(CII*100,2),'% ',round(CIu*100,2),sigID, sep="" )
}

library(gam)
TSage.results = matrix(0,25,3)
rownames(TSage.results) = c("allCauses", "nontraumatic", "resp", "trauma", "cardio", "allergy", "CVA",
"TIa", "heat", "diabetes", "COPD", "asthma", "neuro", "abdo", "metab", "med", "drug", "obgyn",
"psych", "seizure", "febrileseizure", "notrans", "BLStrans", "ALStrans", "othertrans")
colnames(TSage.results) = c("below64","65-84","above85")
TSage.results[1,] = TS3agecat.cause(emsBLS, popuAge3cat, popuName='age3Cat', allDataId=1)
TSage.results[2,] = TS3agecat.cause(emsBLS[emsBLS$NonTraumatic==1,], popuAge3cat,
popuName='age3Cat')
TSage.results[3,] = TS3agecat.cause(emsBLS[emsBLS$Resp==1,], popuAge3cat, popuName='age3Cat')
TSage.results[4,] = TS3agecat.cause(emsBLS[emsBLS$Trauma==1,], popuAge3cat,
popuName='age3Cat')
TSage.results[5,] = TS3agecat.cause(emsBLS[emsBLS$Cardio==1,], popuAge3cat,
popuName='age3Cat')
TSage.results[6,] = TS3agecat.cause(emsBLS[emsBLS$Allergy==1,], popuAge3cat,
popuName='age3Cat')
TSage.results[7,] = TS3agecat.cause(emsBLS[emsBLS$CVA==1,], popuAge3cat, popuName='age3Cat')
TSage.results[8,] = TS3agecat.cause(emsBLS[emsBLS$TIa==1,], popuAge3cat, popuName='age3Cat')
TSage.results[9,] = TS3agecat.cause(emsBLS[emsBLS$Heat==1,], popuAge3cat, popuName='age3Cat')
TSage.results[10,] = TS3agecat.cause(emsBLS[emsBLS$Diabetes==1,], popuAge3cat,
popuName='age3Cat')
TSage.results[11,] = TS3agecat.cause(emsBLS[emsBLS$COPD==1,], popuAge3cat,
popuName='age3Cat')
TSage.results[12,] = TS3agecat.cause(emsBLS[emsBLS$Asthma==1,], popuAge3cat,
popuName='age3Cat')

```

```

TSage.results[13,] = TS3agecat.cause(emsBLS[emsBLS$Neuro==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[14,] = TS3agecat.cause(emsBLS[emsBLS$Abdo==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[15,] = TS3agecat.cause(emsBLS[emsBLS$Metab==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[16,] = TS3agecat.cause(emsBLS[emsBLS$Med==1,], popuAge3cat, popuName='age3Cat')
TSage.results[17,] = TS3agecat.cause(emsBLS[emsBLS$Drug==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[18,] = TS3agecat.cause(emsBLS[emsBLS$OBGYN==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[19,] = TS3agecat.cause(emsBLS[emsBLS$Psych==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[20,] = TS3agecat.cause(emsBLS[emsBLS$Seizure==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[21,] = TS3agecat.cause(emsBLS[emsBLS$FebSeiz==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[22,] = TS3agecat.cause(emsBLS[emsBLS$NoTrans==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[23,] = TS3agecat.cause(emsBLS[emsBLS$BLSTrans==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[24,] = TS3agecat.cause(emsBLS[emsBLS$ALSTrans==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results[25,] = TS3agecat.cause(emsBLS[emsBLS$OtherTrans==1,], popuAge3cat,
  popuName='age3Cat')
TSage.results

```

```

qHum50summer = as.numeric(quantile(emsBLS.date$humidex,0.5) )
opt.thres=40.7

```

```

TS6agecat.cause <- function(datTem, popuIn, popuName, allDataId=0){
  datTem = datTem[datTem$agecat >0,]
  dat.covTem = aggregate(count ~Date + agecat,data=datTem,FUN=sum)
  expGrid = expand.grid(TSdat$Date,c(1:6))
  colnames(expGrid) = c('Date',popuName)
  expGrid = merge(expGrid, TSdat[,c('humidex', 'Date', 'time', 'month', 'Year')],by='Date')
  expGrid = merge(expGrid, popuIn, by=c('Year',popuName))
  expGrid$aboveQ50 = pmax(0, expGrid$humidex - qHum50summer )
  expGrid$belowQ50 = pmin(0, expGrid$humidex - qHum50summer )
  expGrid$aboveThres = pmax(0, expGrid$humidex - opt.thres )
  expGrid$belowThres = pmin(0, expGrid$humidex - opt.thres )
  dat.cov = merge(expGrid,dat.covTem,by=c('Date','agecat'),all=T)
  dat.cov$count[is.na(dat.cov$count)]=0
  dat.cov$logPopu = log(dat.cov$Popu)
  #model 3
  gamMod.age6Cat <- gam(count~ factor(agecat)+ aboveThres* factor(agecat)+
    s(belowThres,df=1)*factor(agecat)+ s(time,df=4)+month + offset(logPopu),family =
    quasi(link=log,variance=mu),data=dat.cov )

  summary.glm(gamMod.age6Cat)

```

```

countByAge3Cat.tem = tapply(datTem$count, datTem$agecat, sum)
countByAge3Cat = rep(0,6)
countByAge3Cat[as.numeric(names(countByAge3Cat.tem))] = countByAge3Cat.tem
popuByAge3Cat = tapply(popuIn$Popu, popuIn$agecat, sum)
callRateByAge3Cat = countByAge3Cat / popuByAge3Cat
tem = rbind(as.integer(countByAge3Cat), as.integer(popuByAge3Cat), round(callRateByAge3Cat, 4))
tem2 = tem
rownames(tem2) = c("calls", "populations", "callRate")
print(tem2)

```

```

ret = rep(0,6)
covLevels = c("0-4", "5-14", "15-44", "45-64", "65-84", "85+")
nLevels = length(covLevels)
tem = tapply(datTem$count, datTem[,popuName], sum, na.rm=T)
tem = tem[!is.na(tem)]
tem2 = tem
tem2 = tem2 / sum(tem2)
cat("Proportion in the total calls", "\n")
print(tem2)

```

```

cat("For ", covLevels[1], "\n")
variables = c('aboveThres')
ret[1] = get.intensity.TSage(gamMod.age6Cat, opt.thres, variables)
cat("For ", covLevels[2], "\n")
variables = c('aboveThres', 'factor(agecat)2:aboveThres')
ret[2] = get.intensity.TSage(gamMod.age6Cat, opt.thres, variables)
cat("For ", covLevels[3], "\n")
variables = c('aboveThres', 'factor(agecat)3:aboveThres')
ret[3] = get.intensity.TSage(gamMod.age6Cat, opt.thres, variables)
cat("For ", covLevels[4], "\n")
variables = c('aboveThres', 'factor(agecat)4:aboveThres')
ret[4] = get.intensity.TSage(gamMod.age6Cat, opt.thres, variables)
cat("For ", covLevels[5], "\n")
variables = c('aboveThres', 'factor(agecat)5:aboveThres')
ret[5] = get.intensity.TSage(gamMod.age6Cat, opt.thres, variables)
cat("For ", covLevels[6], "\n")
variables = c('aboveThres', 'factor(agecat)6:aboveThres')
ret[6] = get.intensity.TSage(gamMod.age6Cat, opt.thres, variables)

ret
}

```

```

TS6age.results = matrix(0, 25, 6)
rownames(TS6age.results) = c("allCauses", "nontraumatic", "resp", "trauma", "cardio", "allergy", "CVA",
" TIA", "heat", "diabetes", "COPD", "asthma", "neuro", "abdo", "metab", "med", "drug", "obgyn",
" psych", "seizure", "febrileseizure", "notrans", "BLStrans", "ALStrans", "othertrans")
colnames(TS6age.results) = c(1:6)
library(gam)
TS6age.results[1,] = TS6agecat.cause(emsBLS, popuAgecat, popuName='agecat', allDataId=1)
TS6age.results[2,] = TS3agecat.cause(emsBLS[emsBLS$NonTraumatic==1,], popuAge3cat,
popuName='age3Cat')

```

```

TS6age.results[3,] = TS6agecat.cause(emsBLS[emsBLS$Resp==1,], popuAgecat, popuName='agecat')
TS6age.results[4,] = TS6agecat.cause(emsBLS[emsBLS$Trauma==1,], popuAgecat, popuName='agecat')
TS6age.results[5,] = TS6agecat.cause(emsBLS[emsBLS$Cardio==1,], popuAgecat, popuName='agecat')
TS6age.results[6,] = TS6agecat.cause(emsBLS[emsBLS$Allergy==1,], popuAgecat, popuName='agecat')
TS6age.results[7,] = TS6agecat.cause(emsBLS[emsBLS$CVA==1,], popuAgecat, popuName='agecat')
TS6age.results[8,] = TS6agecat.cause(emsBLS[emsBLS$TIA==1,], popuAgecat, popuName='agecat')
TS6age.results[9,] = TS6agecat.cause(emsBLS[emsBLS$Heat==1,], popuAgecat, popuName='agecat')
TS6age.results[10,] = TS6agecat.cause(emsBLS[emsBLS$Diabetes==1,], popuAgecat,
  popuName='agecat')
TS6age.results[11,] = TS6agecat.cause(emsBLS[emsBLS$COPD==1,], popuAgecat,
  popuName='agecat')
TS6age.results[12,] = TS6agecat.cause(emsBLS[emsBLS$Asthma==1,], popuAgecat,
  popuName='agecat')
TS6age.results[13,] = TS6agecat.cause(emsBLS[emsBLS$Neuro==1,], popuAgecat, popuName='agecat')
TS6age.results[14,] = TS6agecat.cause(emsBLS[emsBLS$Abdo==1,], popuAgecat, popuName='agecat')
TS6age.results[15,] = TS6agecat.cause(emsBLS[emsBLS$Metab==1,], popuAgecat, popuName='agecat')
TS6age.results[16,] = TS6agecat.cause(emsBLS[emsBLS$Med==1,], popuAgecat, popuName='agecat')
TS6age.results[17,] = TS6agecat.cause(emsBLS[emsBLS$Drug==1,], popuAgecat, popuName='agecat')
TS6age.results[18,] = TS6agecat.cause(emsBLS[emsBLS$OBGYN==1,], popuAgecat,
  popuName='agecat')
TS6age.results[19,] = TS6agecat.cause(emsBLS[emsBLS$Psych==1,], popuAgecat, popuName='agecat')
TS6age.results[20,] = TS6agecat.cause(emsBLS[emsBLS$Seizure==1,], popuAgecat,
  popuName='agecat')
TS6age.results[21,] = TS6agecat.cause(emsBLS[emsBLS$FebSeiz==1,], popuAgecat,
  popuName='agecat')
TS6age.results[22,] = TS6agecat.cause(emsBLS[emsBLS$NoTrans==1,], popuAgecat,
  popuName='agecat')
TS6age.results[23,] = TS6agecat.cause(emsBLS[emsBLS$BLSTrans==1,], popuAgecat,
  popuName='agecat')
TS6age.results[24,] = TS6agecat.cause(emsBLS[emsBLS$ALSTrans==1,], popuAgecat,
  popuName='agecat')
TS6age.results[25,] = TS6agecat.cause(emsBLS[emsBLS$OtherTrans==1,], popuAgecat,
  popuName='agecat')
TS6age.results

```

```

wdTable(as.data.frame(rbind(tapply(emsBLS$count, emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$NonTraumatic==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Resp==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Trauma==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Cardio==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Allergy==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$CVA==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$TIA==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Heat==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Diabetes==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$COPD==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Asthma==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Neuro==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Abdo==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Metab==1), emsBLS$agecat, sum),
  tapply(emsBLS$count*(emsBLS$Med==1), emsBLS$agecat, sum),

```

```

tapply(emsBLS$count*(emsBLS$Drug==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$OBGYN==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$Psych==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$Seizure==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$FebSeiz==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$NoTrans==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$BLSTrans==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$ALSTrans==1), emsBLS$agecat, sum),
tapply(emsBLS$count*(emsBLS$OtherTrans==1), emsBLS$agecat, sum))))

```

```

fitCovariate <- function(cov.any,covName,values,caseOnlyId=1,datIn,agePopuId =0,popuIn =totalking ){
  dat.covTem = aggregate(acount ~ Date + cov.any,data=datIn,FUN=sum)
  idct = dat.covTem[,2] %in% values
  dat.covTem = dat.covTem[idct,]
  colnames(dat.covTem)[2] = covName
  expGrid = expand.grid(TSdat$Date,values)
  colnames(expGrid ) = c('Date',covName)
  dat.cov = merge(expGrid,dat.covTem,by=c('Date',covName),all=T)
  dat.cov$Year = as.numeric(format(dat.cov$Date, format = "%Y"))
  dat.cov$count[is.na(dat.cov$count)]=0
  if (agePopuId==1){
    dat.cov = merge(dat.cov,popuIn,by=c('Year',covName))
  } else {
    dat.cov = merge(dat.cov,totalking,by='Year')
  }
  dat.cov = merge(dat.cov, TSdat[,c('humidex','Date','time','month','dayOfWeek')],by='Date')
  dat.cov$HD = (dat.cov$humidex>opt.thres )*1
  dat.cov$logPopu = log(dat.cov$Popu)

```

### # poisson regression

```

v = dat.cov[,names(dat.cov)==covName]
fit.cov = glm(count~HD*v + s(time,df=5)+ month + offset(logPopu), family =
  quasi(link=log,variance=mu),data=dat.cov)
print(round(summary(fit.cov)$coefficients,4))

```

```

if (caseOnlyId==1){
  # case only logistic regression
  datIn = merge(datIn, TSdat[,c('humidex','Date')],by='Date')
  datIn$HD = datIn$humidex > opt.thres
  v = datIn[,names(datIn)==covName]
  idct = v %in% values
  datT = datIn[idct,]
  datT$v = v[idct]
  datT$v = datT$v==values[2]
  v = rep(datT$v,datT$count)
  HD = rep(datT$HD, datT$count)
  fit.cov.bin = glm(v~HD,family=binomial)
  print(round(summary(fit.cov.bin)$coefficients,4))
}
}

```

```

detach("package:mgcv")
library(gam)
opt.thres=40.7
emsBLS$Year = format(emsBLS$Date,'%Y')

#Counts by covariates
library(plyr)
count(emsBLS, "PatientGenderID")
datTem = emsBLS
covName = 'emerg'
covLevels = c("0","1")
startId =1

TSmod.covariate <- function(datTem, covName, covLevels,startId){
  datTem = datTem[datTem[,covName] %in% covLevels,]
  dat.covTem = aggregate(count ~Date + datTem[,covName],data=datTem,FUN=sum)
  colnames(dat.covTem) = c('Date',covName,'count')
  expGrid = expand.grid(TSdat$Date[startId:nDays],covLevels)
  colnames(expGrid) = c('Date',covName)
  # add population and humidex , add year
  expGrid = merge(expGrid, TSdat[,c('humidex','Date','time','month','Year','logPopu')],by='Date')
  expGrid$aboveQ50 = pmax(0, expGrid$humidex - qHum50summer )
  expGrid$belowQ50 = pmin(0, expGrid$humidex - qHum50summer )
  expGrid$aboveThres = pmax(0, expGrid$humidex - opt.thres )
  expGrid$belowThres = pmin(0, expGrid$humidex - opt.thres )
  #expGrid$I2009plus <- countyMorb2.date$Date > "2008-09-27"
  # merge morbidity count and expand grid
  dat.cov = merge(expGrid,dat.covTem,by=c('Date',covName),all=T)
  dat.cov$count[is.na(dat.cov$count)]=0

  v = dat.cov[,covName]
  #gamMod.cov<- gam(adm_count ~ v+ belowThres*v+ aboveThres*v
  #          + s(time,df=163) + month + dayOfWeek +offset( logPopu ),family =
quasi(link=log,variance=mu),data=dat.cov)
  #model 3
  gamMod.cov <- gam(count~ v+aboveThres*v + s(belowThres,df=1)*v+ s(time,df=4) + month+
    + offset( logPopu ), family = quasi(link=log,variance=mu),data=dat.cov )

  print(summary.glm(gamMod.cov))

  # significant?
  nLevels = length(covLevels)
  tem = tapply(datTem$count, datTem[,covName],sum, na.rm=T)
  tem = tem[!is.na(tem)]
  print(tem/sum(tem))

  cat("For ", covLevels[1],'\n')
  variables = c('aboveThres')
  get.intensity.TSage(gamMod.cov,opt.thres,variables)

  for (i in 2:nLevels){

```

```

variables = c('aboveThres',paste('v',covLevels[i],':aboveThres',sep=""))
cat("For ", covLevels[i],'\n')
get.intensity.TSage(gamMod.cov,opt.thres,variables)
}

```

### # difference

```

variables = c(paste('v',covLevels[2],':aboveThres',sep=""))
cat("For ", covLevels[2],'compared to', covLevels[1],'\n')
get.intensity.TSage(gamMod.cov,opt.thres,variables)
}

```

```
TSmod.covariate(emsBLS, covName = 'sex',covLevels = c("F","M"),startId = 1)
```

## Effect Modification and Effects of Heat Characteristics

### ## cool down effect

```

qHum50summer = as.numeric(quantile(emsBLS.date$humidex,0.5) )
TSdat = emsBLS.date
opt.thres = 40.7
TSdat$belowQ50 = pmin(0,(TSdat$humidex-qHum50summer))
TSdat$belowThres = pmin(0,(TSdat$humidex-opt.thres))
TSdat$aboveQ50 = pmax(0,(TSdat$humidex-qHum50summer))
TSdat$aboveThres = pmax(0,(TSdat$humidex-opt.thres))
sum(TSdat$humidex>opt.thres)

```

```
TSdat$cooldown = (TSdat$humidex>opt.thres)*1*(TSdat$humidex - TSdat$countyHumidexMin)
```

### #model 3

```

gamMod.cool <- gam(count~ s(time,df=4)+month + aboveThres + s(belowThres,df=1) +cooldown +
  offset( logPopu ), family = quasi(link=log,variance=mu),data=TSdat)

```

```

summary.glm(gamMod.cool)
get.intensity(gamMod.cool,opt.thres,1)

```

### ## Duration effect

```

TSdat$HD = (TSdat$humidex>opt.thres)*1
TSdat$duration[1] = tem = TSdat$HD[1]
for (i in 2:nDays){
  if (TSdat$HD[i] == 0) TSdat$duration[i]= tem = 0 else TSdat$duration[i] = tem =tem+1
}

```

### #model 3

```

gamMod.dur <- gam(count~ s(time,df=4)+month + aboveThres + s(belowThres,df=1) + duration +
  offset( logPopu ), family = quasi(link=log,variance=mu), data=TSdat)

```

```

summary.glm(gamMod.dur)
get.intensity(gamMod.dur,opt.thres,1)

```

## **APPENDIX 7:**

### **METHODS—COST ANALYSIS**

The cost analysis quantified the impact of the association between extreme heat and EMS calls on county resources by providing a financial measure of comparison. Data used for this analysis included the average daily calls on heat days and non-heat days from the relative risk analyses as well as total call counts and total annual costs for BLS and ALS calls from the Public Health Seattle and King County Division of Emergency Medical Services 2012 Annual Report [PHSKC 2012]. Average BLS and ALS costs were calculated as the total cost for 2011 divided by the total number of calls for 2011. This produced average costs per call of \$104.7 and \$962.8 for BLS and ALS calls, respectively. The total costs for an average heat day and an average non-heat day were then calculated using the average call counts per day for all three relative risk analyses; BLS at the 95<sup>th</sup> percentile, BLS at the 99<sup>th</sup> percentile, and ALS at the 99<sup>th</sup> percentile. Only data for all ages from all causes, trauma, and non-trauma were used for this comparison.

## APPENDIX 8:

### DATA EXPLORATION

Exploration of the meteorological data (alone and with EMS outcomes) strongly relied on the creation of figures as they provide valuable visual forms of data exploration as well as quality assurance and control measures.

#### Figures

- 8.1—Scatterplots of King County EMS calls per day by humidex
- 8.2— Scatterplot of King County BLS EMS calls per day by humidex with spline with two knots
- 8.3—Combined trend plots of call counts and humidex for entire study timeframe.
- 8.4—Average maximum humidex for King County in 2009
- 8.5—Duration effects: Number of calls by duration
- 8.6—Duration: Humidex by duration
- 8.7—Cool down effects: Number of average calls per day by difference in avg. daily max and min humidex
- 8.8—Cool down effects: Difference in daily average maximum and minimum humidex by average maximum humidex
- 8.9—Cool down effects: Average daily minimum humidex by average daily maximum humidex
- 8.10—Fine tuning slopes
- 8.11—Time Series analysis threshold selection

Figure 8.1 depicts the number of calls per day by average county-wide maximum humidex value for the BLS and ALS datasets. These figures show a positive correlation between the number of calls and maximum humidex starting from approximately 25 °C humidex. Below that value, the slope is positive for the BLS data while relatively flat for ALS data. Additionally, the BLS data is clustered more closely to the trendline and appears to have a steeper slope than the ALS data. Figure 8.2 adds a spline with two knots, one at the 50<sup>th</sup> percentile and the other at the optimal threshold for the BLS data in the time series analysis.

Figure 8.3 is the combined trend plot for call counts and humidex by day for the entire study timeframe for BLS and ALS data. Both plots illustrate closely matched trends between call counts and humidex, with high humidex associated with a high call volume and vice versa,

although the BLS data appears to be a better match than the ALS. Of particular interest is the high peak during the 2009 heat wave that shows a drastic increase in calls. Since this extreme heat has some of the highest humidex values in the timeframe, Figure 8.4 illustrates humidex for this season alone with clearly defined 95<sup>th</sup> and 99<sup>th</sup> percentiles. As is clearly evident from that figure, the July heat is the only heat that season above the 99<sup>th</sup> percentile, but it contains 6 days at that elevated humidex. Other distinct peaks in the data fall above the 95<sup>th</sup> percentile as would be expected.

Figures 8.5 and 8.6 describe the duration of heat. Figure 8.5 shows an overall increase in the number of calls per day with increasing duration, although both graphs set at the 99<sup>th</sup> percentile show a clear decrease in the number of calls on day 2. This observation is peculiar given the clear increase in humidex with increase in duration seen in Figure 8.6.

Figures 8.8 and 8.9 show increasing cool down temperature difference as well as increasing average daily minimum humidex with increasing average daily maximum humidex. This is important as it shows that while the difference in high to low daily humidex may increase with humidex, it does not increase enough to cause daily minimum humidex values to reflect a negative slope.

Figures 8.10 and 8.11 shows slope and threshold selection for the time series models. The AICs for BLS and ALS data in figure 8.11 are interesting as they show a non monotonic slope with two distinct low AICs; the first around the 99<sup>th</sup> percentile and the second, lowest AIC, at the selected thresholds of 40.7 and 39.7 C.

**Figure 8.1: Scatterplots of King County EMS calls per day by humidex. Top figure is BLS data and bottom figure is ALS data.**

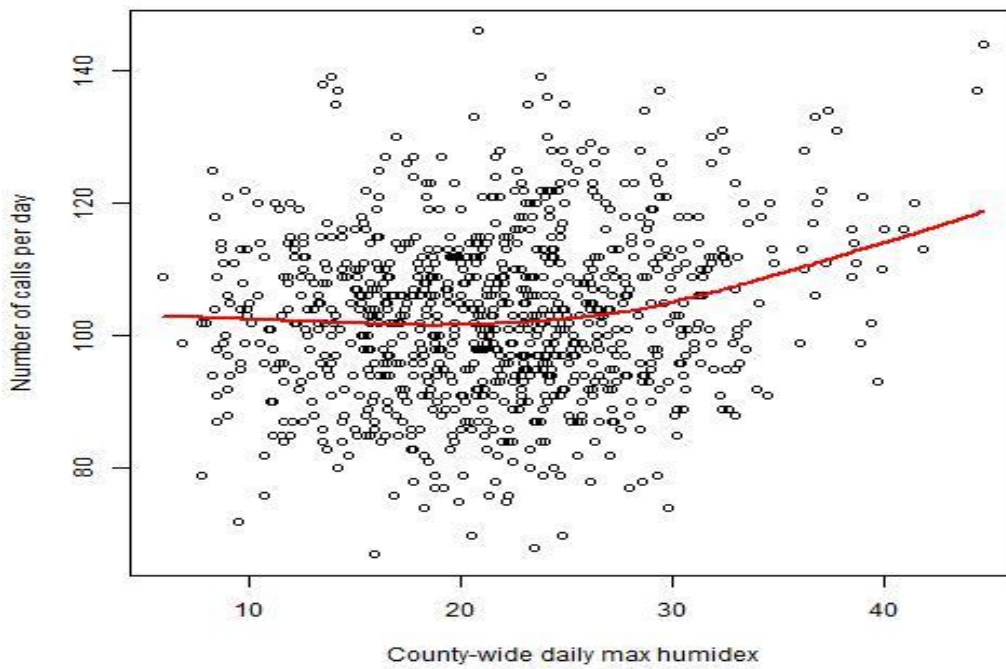
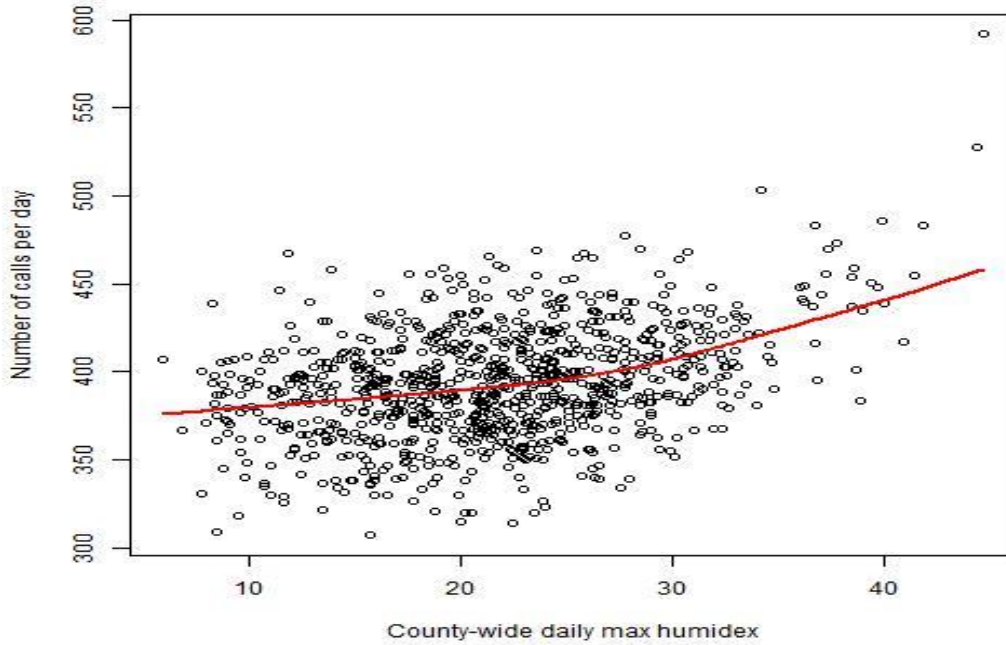
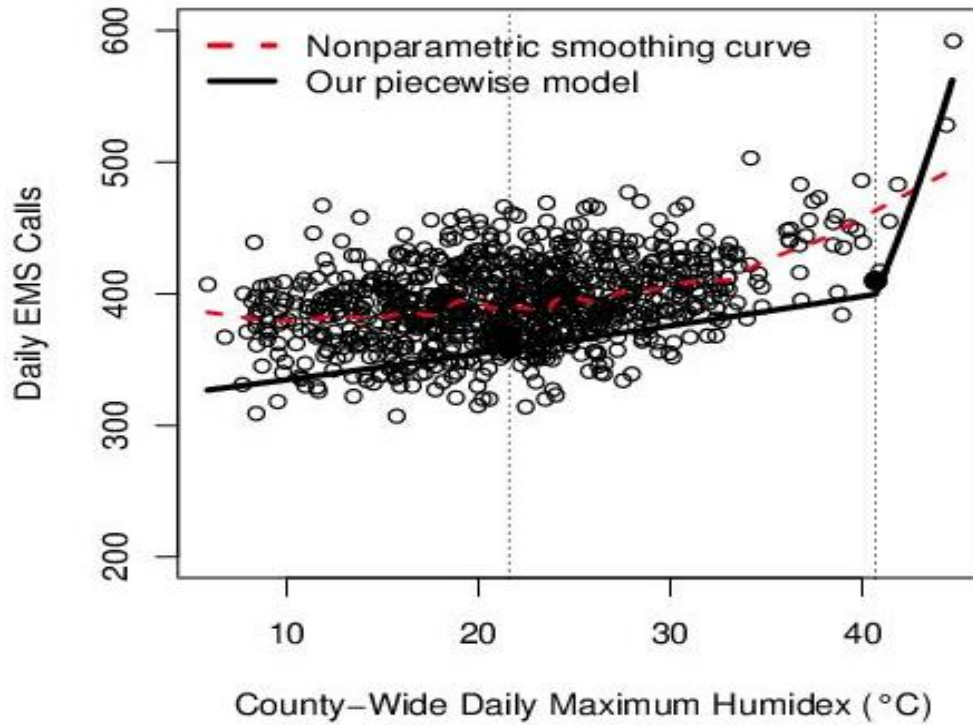
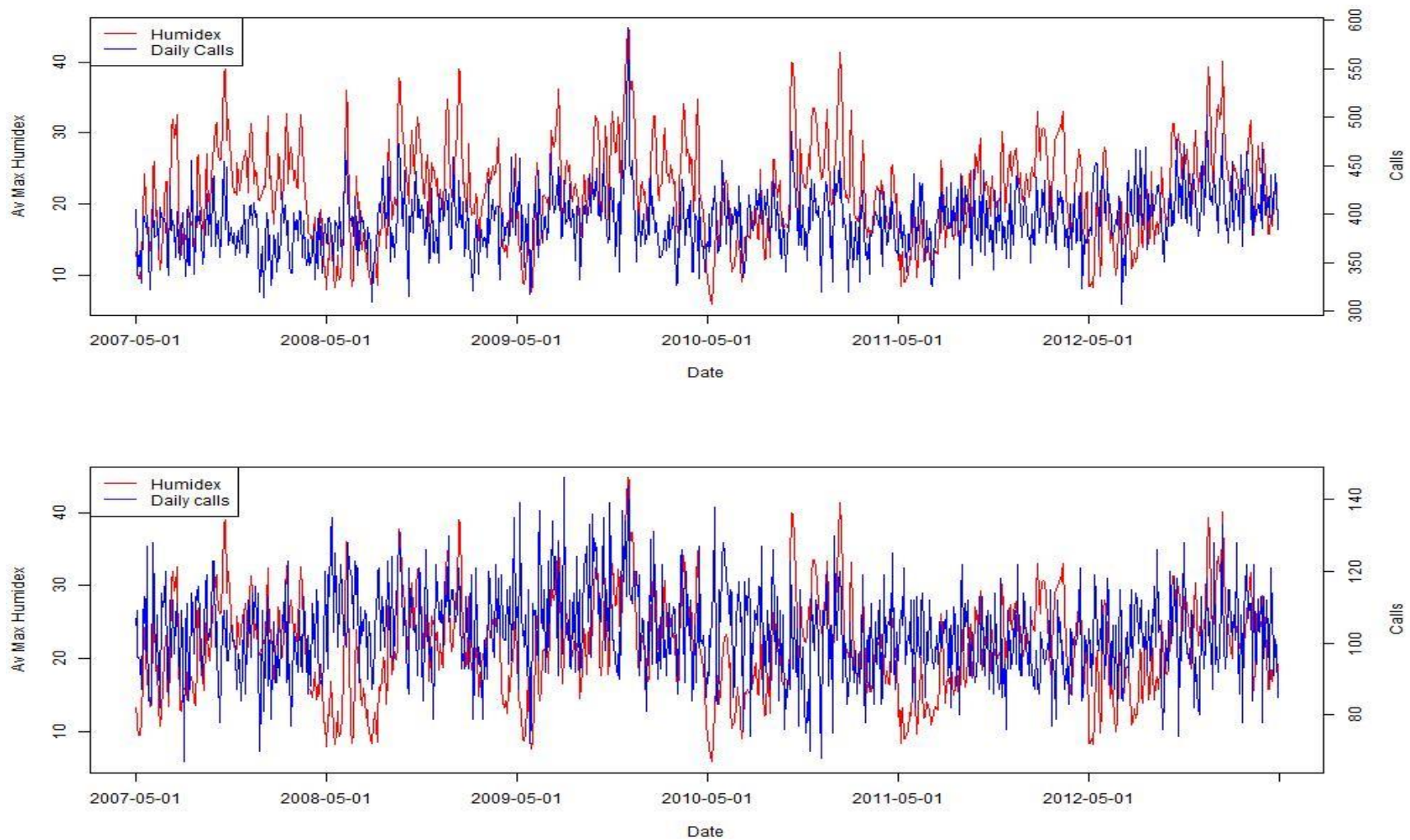


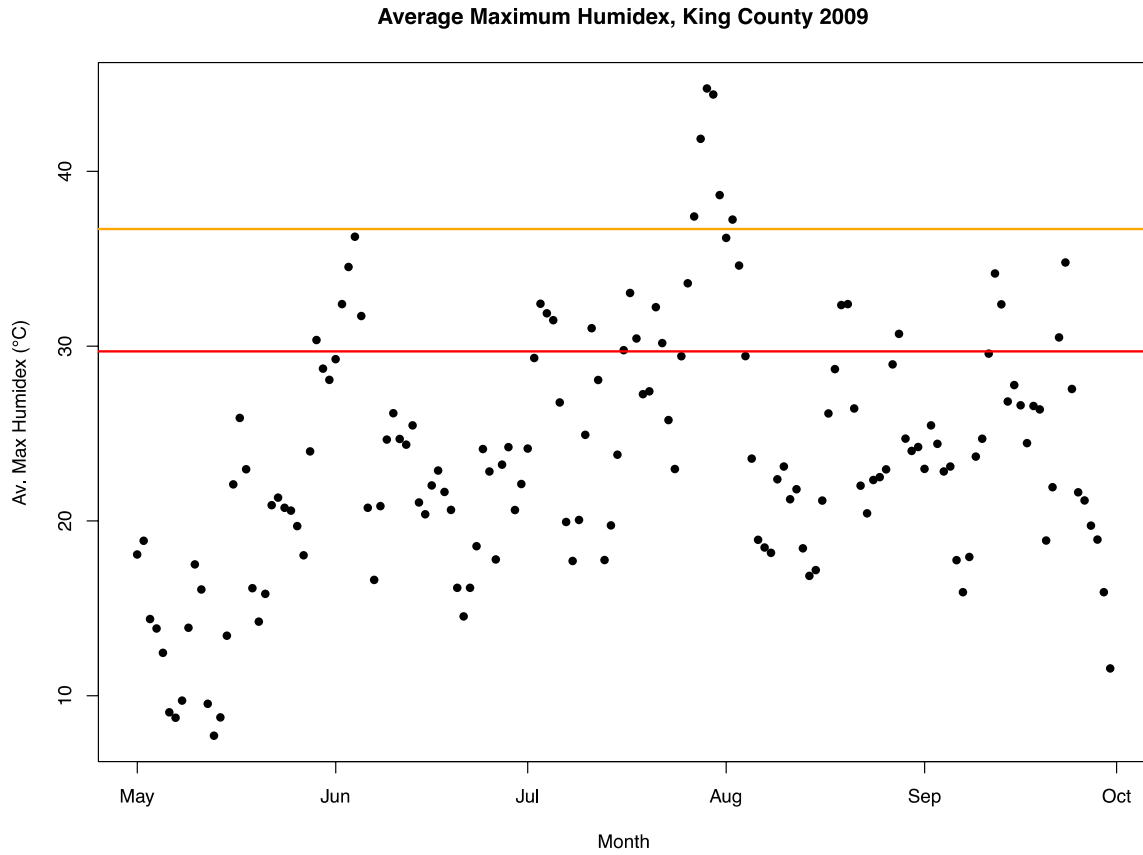
Figure 8.2: Scatterplot of King County BLS EMS calls per day by humidex with spline with two knots (50<sup>th</sup> percentile and optimal time series threshold).



**Figure 8.3: Combined trend plots of call counts and humidex for entire study timeframe. Top figure is for BLS data and bottom figure is for ALS data.**



**Figure 8.4: Average Maximum Humidex, King County 2009. Red line indicates 95<sup>th</sup> percentile threshold (29.7 °C) and orange line indicates 99<sup>th</sup> percentile threshold (36.7 °C).**



**Figure 8.5: Duration effect for BLS at 95<sup>th</sup> and 99<sup>th</sup> percentile thresholds and ALS data at 99<sup>th</sup> percentile threshold with trendline: Number of calls per day by duration. BLS data is on the top, with the 95<sup>th</sup> percentile on the left and the 99<sup>th</sup> percentile on the right. ALS data is on the bottom.**

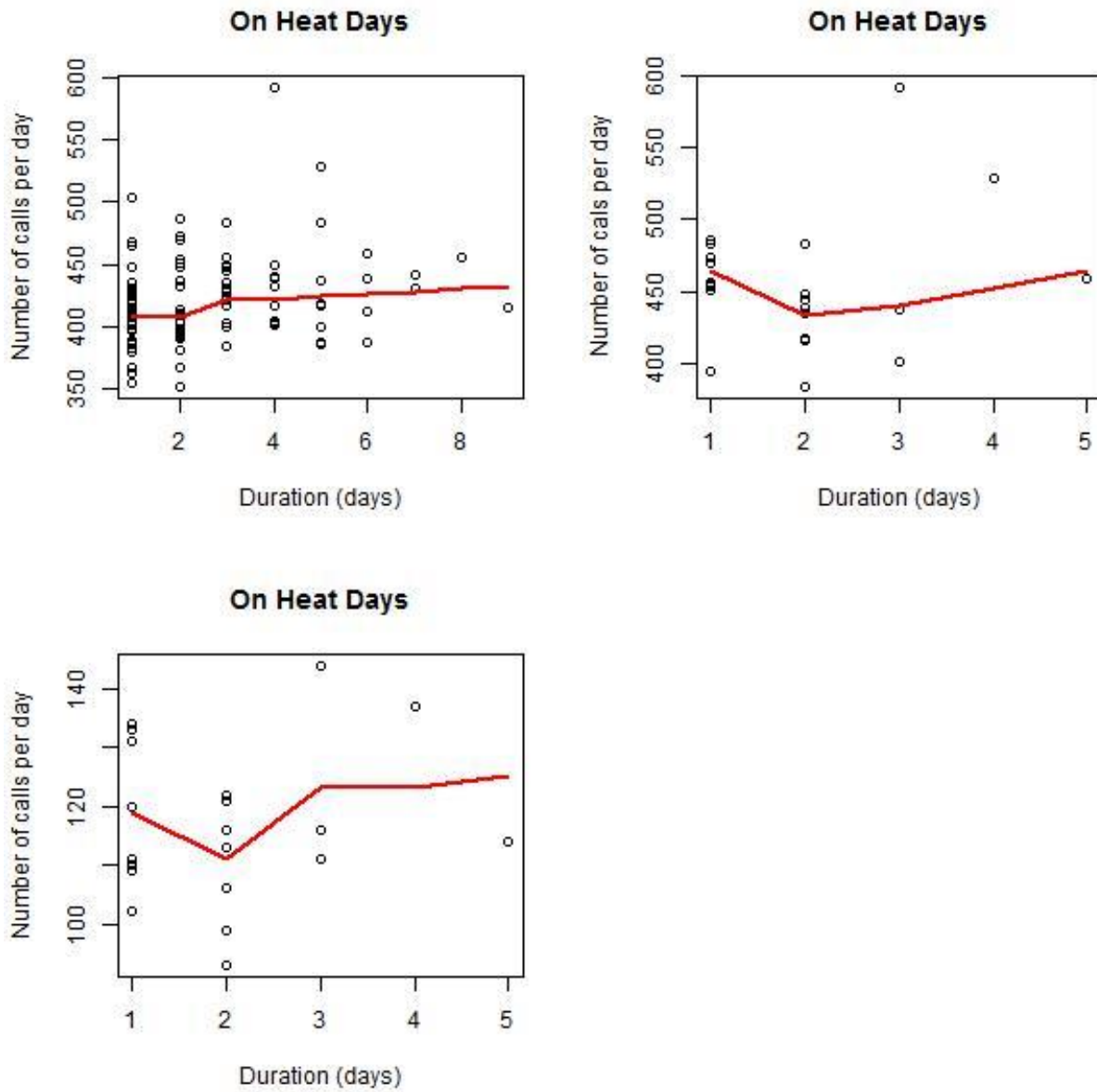
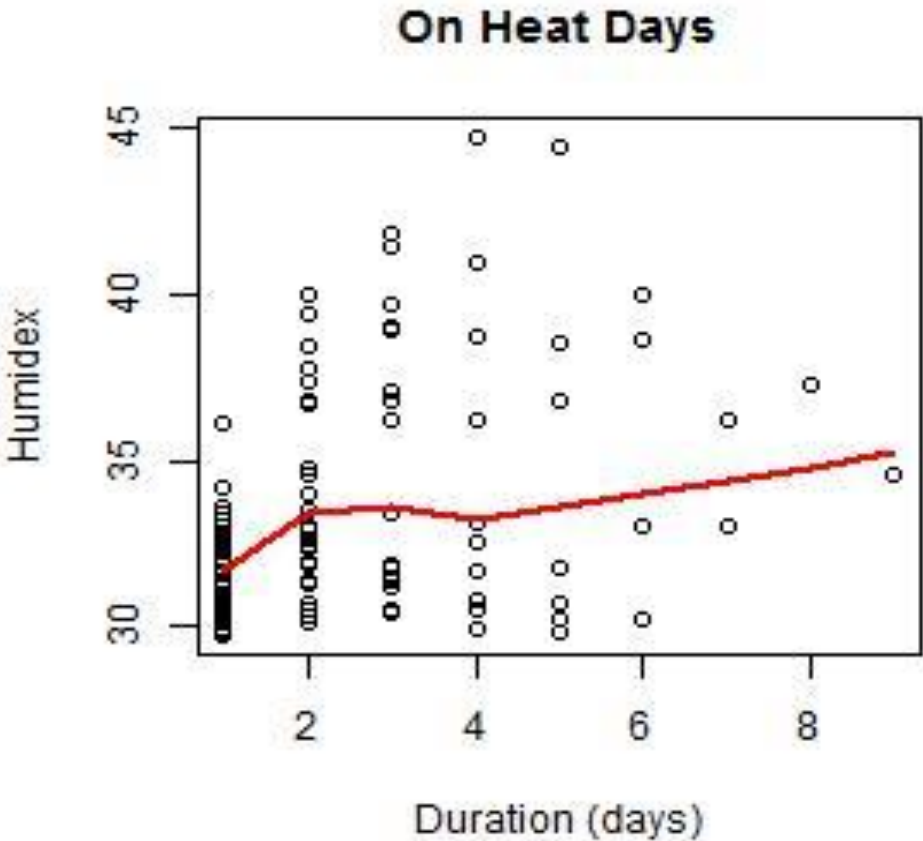


Figure 8.6: Duration effect for BLS and ALS data: Average daily maximum humidex by duration.



**Figure 8.7: Cool down effect for BLS at 95<sup>th</sup> and 99<sup>th</sup> percentile thresholds and ALS data at 99<sup>th</sup> percentile threshold with trendline.**

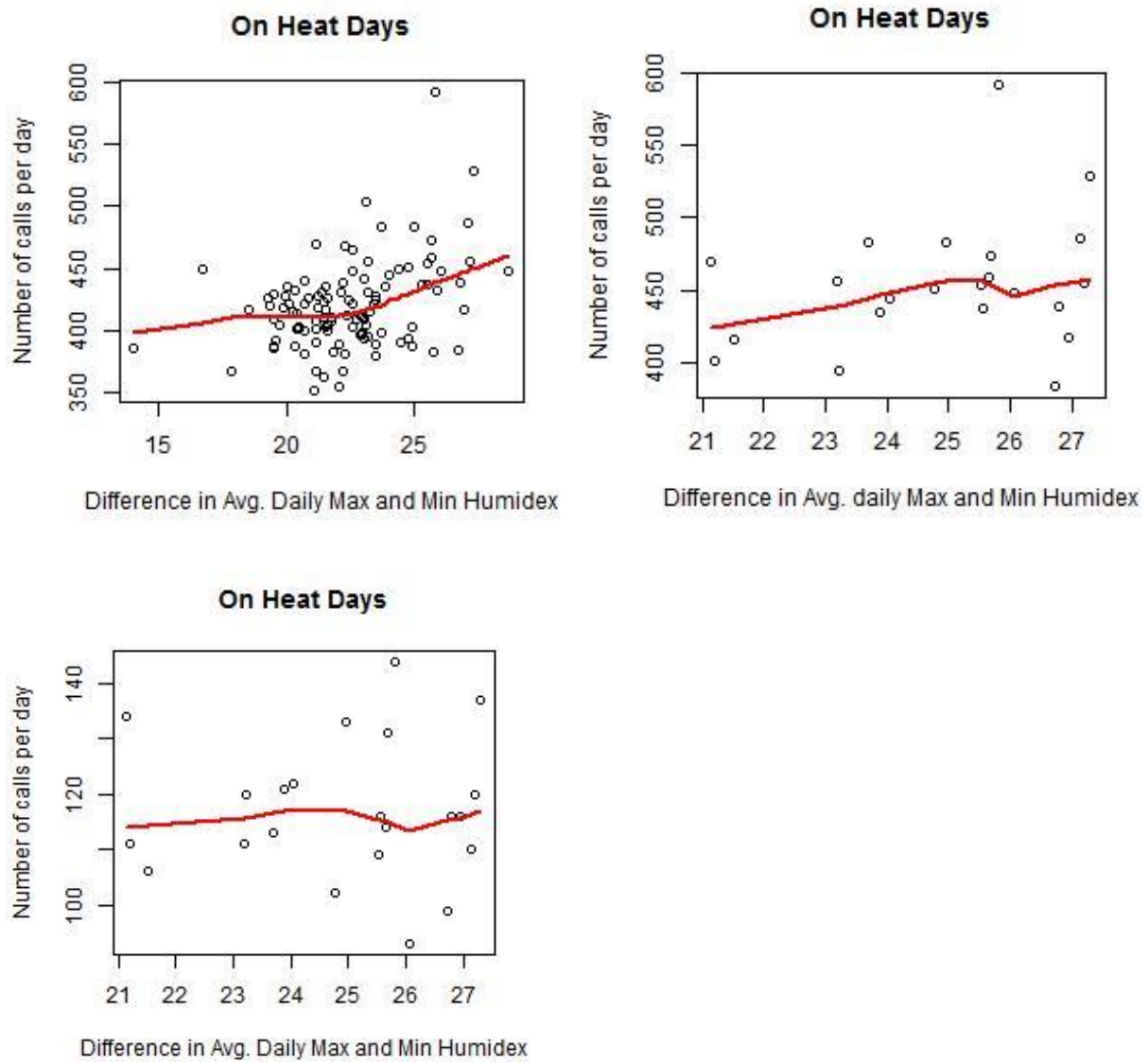


Figure 8.8: Cool down effect for BLS at 95<sup>th</sup> and 99<sup>th</sup> percentile thresholds and ALS data at 99<sup>th</sup> percentile threshold with trendline.

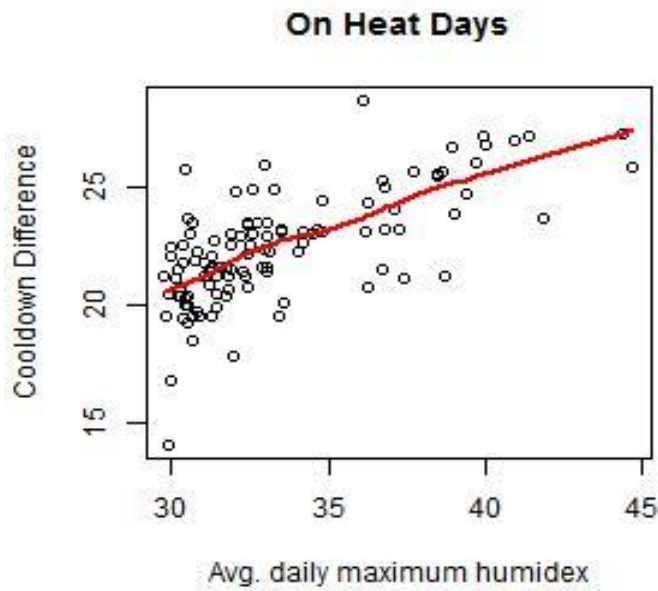
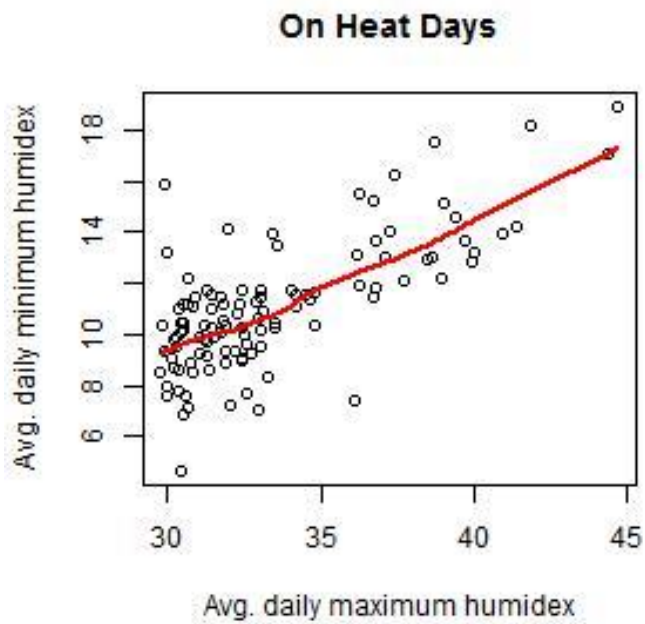
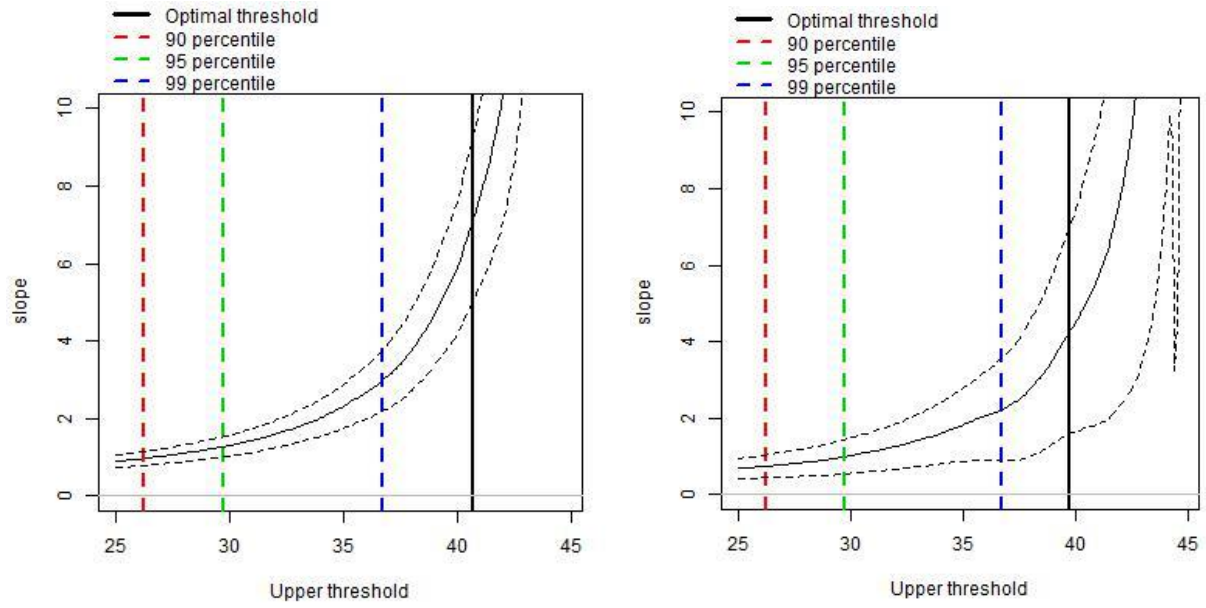


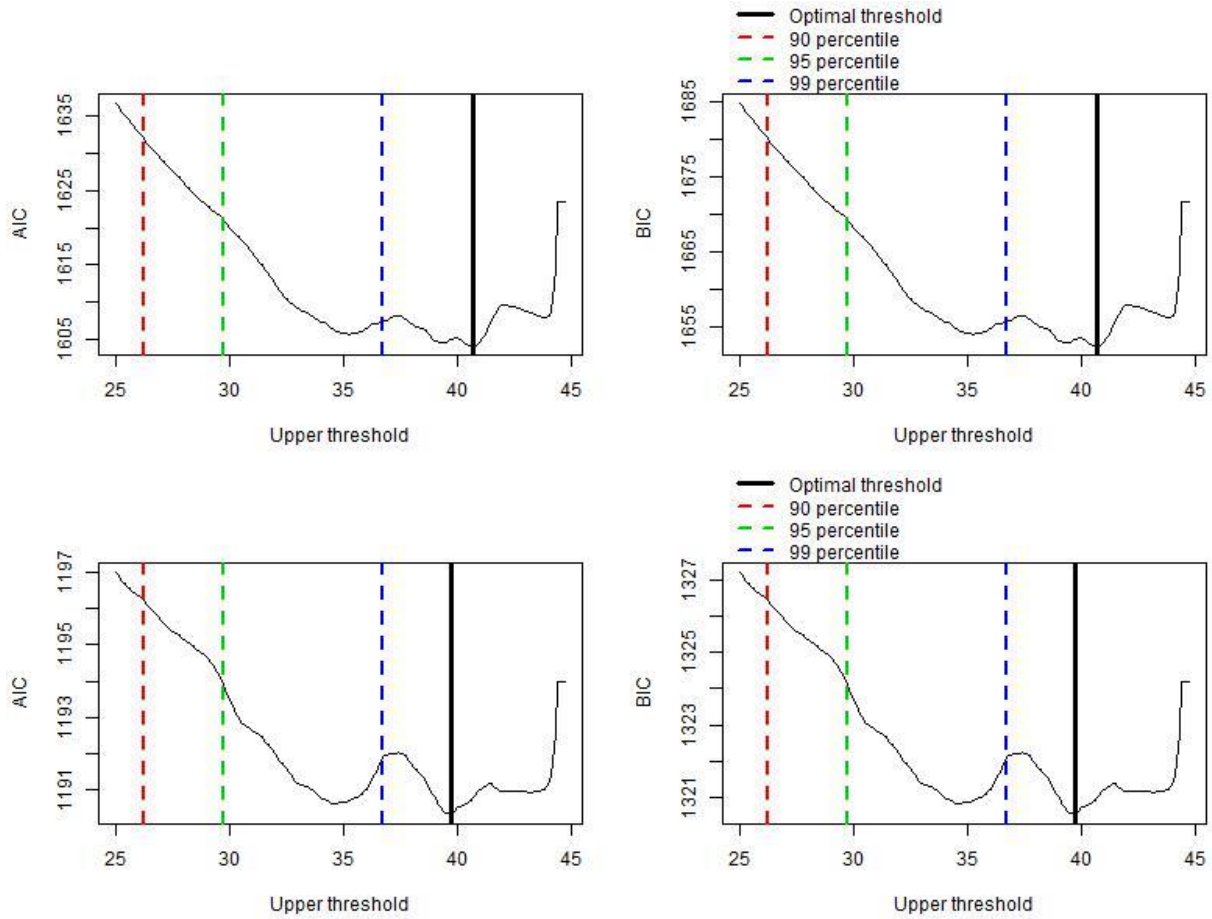
Figure 8.9: Cool down effect for BLS at 95<sup>th</sup> and 99<sup>th</sup> percentile thresholds and ALS data at 99<sup>th</sup> percentile threshold with trendline.



**Figure 8.10: Fine-tuning of slopes for times series model. BLS is on left and ALS is on right.**



**Figure 8.11: Threshold selection for time series analyses. The top figures depict BLS data and the bottom figures depict ALS data.**



## APPENDIX 9:

### RESULTS—RELATIVE RISK ANALYSIS

The relative risk (RR) analysis results presented below include BLS data with a humidex threshold at the 95<sup>th</sup> percentile (29.7 °C) as well as both the BLS and ALS data with a humidex threshold at the 99<sup>th</sup> percentile (36.7 °C). Since the BLS and ALS data differed in the threshold with the best model fit (95<sup>th</sup> and 99<sup>th</sup> percentiles, respectively), the BLS data was of primary interest in this analysis, and both thresholds were relevant to other recent work [Busch Isaksen et al. 2014], the BLS data was presented with both thresholds. All relative risk results were presented by age category for medical issue and level of transportation. Additionally, results for the analyses of the effects of extreme heat characteristics were included, as a sensitivity analysis for the exclusion of missing age and gender data.

#### List Of Tables:

- 9.1—RR for BLS and ALS for all cause, trauma, and non-trauma
- 9.2—RR for BLS data at 95<sup>th</sup> percentile
- 9.3— RR for BLS data at 99<sup>th</sup> percentile
- 9.4— RR for ALS data at 99<sup>th</sup> percentile
- 9.5—RR for BLS and ALS for transportation
- 9.6—Call count for BLS and ALS transportation
- 9.7—Total call counts for BLS data at 95<sup>th</sup> percentile
- 9.8—Total call counts for BLS data at 99<sup>th</sup> percentile
- 9.9—Total call counts for ALS data at 99<sup>th</sup> percentile
- 9.10—Average call counts for BLS and ALS data
- 9.11—Duration and cool down effects
- 9.12—Sensitivity Analysis

#### Health Outcomes

Significant results for all ages and by age group for all causes, non-trauma, and trauma are listed in Table 9.1. The risk of an EMS call on a heat day compared to a non-heat day increased for all causes, all ages in all three analyses. The magnitude of this increase was greater for the analyses at the 99<sup>th</sup> percentile than the 95<sup>th</sup> percentile with an 8% (95% CIs: 6%, 9%)

increase in calls on a 95<sup>th</sup> (29.7 °C) percentile heat day compared to a non heat day for the BLS data, a 16% (95% CIs: 13%, 20%) increase on a 99<sup>th</sup> (36.7 °C) percentile heat day compared to a non-heat day for the BLS data, and a 14% (95% CIs: 9%, 20%) increase on a 99<sup>th</sup> (36.7 °C) percentile heat day compared to a non-heat day for the ALS data. Significant increases in risk were also identified in all three analyses for non-trauma, all ages of 6% (95% CIs: 4%, 8%) for BLS data at the 95<sup>th</sup> percentile, 16% (95% CIs: 13%, 20%) for the BLS data at the 99<sup>th</sup> percentile, and 13% (95% CIs: 7%, 19%) for the ALS. Significant results for trauma in all ages only resulted from the BLS analyses, where there was a 13% (95% CIs: 7%, 18%) increase in calls at the 95<sup>th</sup> percentile and 11% increase (95% CIs: 0%, 24%) at the 99<sup>th</sup> percentil. Every age group had at least one analysis with statistically significant results: 15-44 and 45-64 year olds had the most consistent occurrence of significant increases in risk across all, trauma, and non-trauma causes and both BLS and ALS datasets.

Significant results by age group include all causes and non trauma in 15-44 year olds and 45-64 year olds for all three analyses; trauma in 0-4 year olds and 15-44 year olds in both BLS analyses; and all causes and non-trauma in 0-4 year olds and 65-84 year olds in both BLS analyses. The only significant results for the 85+ age group are found in all causes and non-trauma groups from both analyses using the 99<sup>th</sup> percentile. 5-14 year olds only had a significant effect for all causes in the BLS 95<sup>th</sup> percentile analysis and for non-trauma from the ALS analysis (which showed a protective effect).

For subcategories of health effects, analysis of all ages reveals statistically significant increases in risk (95% CIs) of a BLS call on a 95<sup>th</sup> percentile heat day compared to a non heat day of 4% for abdominal/genito-urinary, 8% for alcohol/drug, 14% for anaphylaxis/allergy reaction, 11% for metabolic/endocrine, 8% for diabetes, 3% for neurological, 17% for other

Table 9.1: Relative risk analysis results for BLS and ALS data. Data presented as increased risk (95% CIs) of an EMS call on a 95th percentile (29.7 °C) or a 99th percentile (36.7 °C) heat day compared to a non-heat day. Data displayed by age category for all causes, trauma, and non-trauma <sup>1</sup>				
		All Cause	Trauma	Non-Trauma
All Ages	BLS 95th	<b>1.08 (1.06, 1.09)</b>	<b>1.13 (1.07, 1.18)</b>	<b>1.06 (1.04, 1.08)</b>
	BLS 99th	<b>1.16 (1.13, 1.2)</b>	<b>1.11 (1, 1.24)</b>	<b>1.16 (1.13, 1.2)</b>
	ALS 99th	<b>1.14 (1.09, 1.2)</b>	1.13 (0.91, 1.17)	<b>1.13 (1.07, 1.19)</b>
0-4	BLS 95th	<b>1.14 (1.07, 1.21)</b>	<b>1.35 (1.18, 1.54)</b>	<b>1.09 (1, 1.18)</b>
	BLS 99th	<b>1.22 (1.07, 1.39)</b>	<b>1.33 (1.01, 1.79)</b>	<b>1.18 (1, 1.4)</b>
	ALS 99th	1.09 (0.82, 1.45)	1.47 (0.77, 2.79)	0.98 (0.7, 1.37)
5-14	BLS 95th	<b>1.07 (1, 1.14)</b>	1.11 (0.98, 1.25)	1.04 (0.95, 1.14)
	BLS 99th	0.91 (0.79, 1.05)	0.84 (0.63, 1.13)	0.88 (0.71, 1.09)
	ALS 99th	0.78 (0.55, 1.11)	0.97 (0.46, 2.03)	<b>0.61 (0.38, 0.99)<sup>2</sup></b>
15-44	BLS 95th	<b>1.11 (1.08, 1.13)</b>	<b>1.16 (1.09, 1.23)</b>	<b>1.09 (1.06, 1.12)</b>
	BLS 99th	<b>1.19 (1.14, 1.25)</b>	<b>1.16 (1.01, 1.33)</b>	<b>1.22 (1.16, 1.28)</b>
	ALS 99th	<b>1.18 (1.08, 1.28)</b>	1.17 (0.93, 1.47)	<b>1.13 (1.03, 1.25)</b>
45-64	BLS 95th	<b>1.09 (1.07, 1.12)</b>	<b>1.12 (1.05, 1.2)</b>	<b>1.07 (1.05, 1.1)</b>
	BLS 99th	<b>1.17 (1.11, 1.22)</b>	1.06 (0.91, 1.23)	<b>1.17 (1.11, 1.23)</b>
	ALS 99th	<b>1.2 (1.11, 1.29)</b>	1.16 (0.83, 1.61)	<b>1.19 (1.1, 1.29)</b>
65-84	BLS 95th	<b>1.05 (1.03, 1.08)</b>	1.15 (0.97, 1.37)	<b>1.03 (1.01, 1.07)</b>
	BLS 99th	<b>1.15 (1.09, 1.21)</b>	1.15 (0.97, 1.37)	<b>1.13 (1.06, 1.2)</b>
	ALS 99th	1.09 (0.99, 1.19)	0.87 (0.48, 1.55)	1.09 (0.99, 1.2)
85+	BLS 95th	1.02 (0.99, 1.05)	1.07 (0.89, 1.29)	1.02 (0.98, 1.06)
	BLS 99th	<b>1.14 (1.07, 1.21)</b>	1.07 (0.89, 1.29)	<b>1.13 (1.05, 1.22)</b>
	ALS 99th	<b>1.13 (1, 1.26)</b>	0.75 (0.28, 2)	<b>1.13 (1, 1.27)</b>

medical, and 243% for heat illness and dehydration. By age group, all 6 groups resulted in statistically significant increases in risk in the other medical and heat and dehydration categories; 45-64 year olds have an increased risk from metabolic/endocrine, diabetes, alcohol/drug, and anaphylaxis/allergy reaction; 65-84 year olds have an increased risk for metabolic/endocrine and diabetes, 15-45 year olds are at increased risk from psychological and neurological effects, and 85+ are at increased risk for metabolic/endocrine effects. Please see table 9.2. For a 99<sup>th</sup> percentile heat day the BLS data shifted slightly to affect the older population more. Please see table 9.3.

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ )

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [1136 cases on non-heat days, 17 cases on a heat day]

Table 9.2: Relative risk analysis results for BLS data. Data presented as increased risk (95% CIs) of an EMS call on a 95th percentile (29.7 °C) heat day compared to a non-heat day. Data displayed by age category, and medical issue.<sup>1</sup>

Medical Issue	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
All Causes	<b>1.08 (1.06, 1.09)</b>	<b>1.14 (1.07, 1.21)</b>	<b>1.07 (1, 1.14)</b>	<b>1.11 (1.08, 1.13)</b>	<b>1.09 (1.07, 1.12)</b>	<b>1.05 (1.03, 1.08)</b>	1.02 (0.99, 1.05)
Trauma	<b>1.13 (1.07, 1.18)</b>	<b>1.35 (1.18, 1.54)</b>	1.11 (0.98, 1.25)	<b>1.16 (1.09, 1.23)</b>	<b>1.12 (1.05, 1.2)</b>	1.15 (0.97, 1.37)	1.07 (0.89, 1.29)
Non-Trauma	<b>1.06 (1.04, 1.08)</b>	<b>1.09 (1, 1.18)</b>	1.04 (0.95, 1.14)	<b>1.09 (1.06, 1.12)</b>	<b>1.07 (1.05, 1.1)</b>	<b>1.03 (1.01, 1.07)</b>	1.02 (0.98, 1.06)
Abdominal/Genito-Urinary	<b>1.04 (1, 1.08)</b>	1.15 (0.81, 1.64)	1.25 (0.96, 1.62)	1.04 (0.98, 1.11)	<b>1.07 (1, 1.14)</b>	0.98 (0.9, 1.07)	1.02 (0.91, 1.14)
Alcohol/Drugs	<b>1.08 (1.03, 1.14)</b>	1.11 (0.82, 1.51)	1.07 (0.74, 1.54)	1.06 (0.99, 1.13)	<b>1.13 (1.04, 1.23)</b>	1.01 (0.84, 1.2)	1.19 (0.84, 1.69)
Anaphylaxis/Allergy	<b>1.14 (1.02, 1.27)</b>	1.29 (0.96, 1.73)	0.93 (0.67, 1.28)	1.07 (0.9, 1.26)	<b>1.23 (1.01, 1.51)</b>	1.24 (0.94, 1.63)	1.12 (0.71, 1.71)
Cardiovascular	0.97 (0.93, 1.01)	1.61 (0.92, 2.83)	0.45 (0.19, 1.1)	0.99 (0.88, 1.1)	1.03 (0.97, 1.1)	0.93 (0.87, 0.99)	0.93 (0.85, 1.02)
Metabolic/Endocrine	<b>1.11 (1.04, 1.18)</b>	1.23 (0.47, 3.19)	1.2 (0.6, 2.44)	0.98 (0.86, 1.11)	<b>1.15 (1.04, 1.27)</b>	<b>1.18 (1.05, 1.32)</b>	<b>1.12 (1.05, 1.19)</b>
Diabetes	<b>1.08 (1.01, 1.16)</b>	0.77 (0.17, 3.5)	1.19 (0.5, 2.83)	0.92 (0.79, 1.07)	<b>1.14 (1.02, 1.28)</b>	<b>1.16 (1.02, 1.32)</b>	1 (0.74, 1.35)
Neurological	<b>1.03 (1, 1.06)</b>	1 (0.87, 1.15)	0.99 (0.83, 1.17)	<b>1.06 (1, 1.12)</b>	1.03 (0.97, 1.09)	1.02 (0.97, 1.08)	0.99 (0.92, 1.07)
Suspected CVA	0.97 (0.89, 1.05)	0.57 (0.06, 4.95)	--	1.2 (0.85, 1.71)	0.94 (0.8, 1.12)	0.97 (0.86, 1.1)	0.96, 0.83, 1.11)
Suspected TIA	<b>0.6 (0.42, 0.85)</b>	1 (0.82, 1.22)	1 (0.82, 1.22)	--	0.7 (0.37, 1.36)	0.64 (0.4, 1.02)	<b>0.57 (0.34, 0.96)<sup>2</sup></b>
Seizures	1.01 (0.95, 1.08)	1.09 (0.87, 1.37)	0.96 (0.76, 1.22)	1.03 (0.94, 1.12)	1.03 (0.92, 1.15)	0.85 (0.68, 1.08)	0.91 (0.6, 1.37)
Febrile Seizures	0.96 (0.8, 1.15)	0.96 (0.79, 1.16)	1.2 (0.55, 2.6)	0.67 (0.16, 2.79)	1.64 (0.56, 4.76)	1.48 (0.17, 12.76)	0.35 (0.05, 2.58)
OBGYN	1.06 (0.95, 1.19)	0.87 (0.29, 2.59)	0.67 (0.07, 6.04)	1.07 (0.95, 1.2)	1.15 (0.65, 2.02)	0.53 (0.12, 2.38)	0.95 (0.37, 2.41)
Other Medical	<b>1.17 (1.13, 1.2)</b>	<b>1.22 (1.05, 1.42)</b>	<b>1.26 (1.06, 1.49)</b>	<b>1.24 (1.18, 1.31)</b>	<b>1.14 (1.09, 1.2)</b>	<b>1.16 (1.1, 1.21)</b>	<b>1.12 (1.05, 1.19)</b>
Heat Illness & Dehydration	<b>3.43 (3.07, 3.84)</b>	<b>3.89 (2.08, 7.29)</b>	<b>4.22 (2.67, 6.69)</b>	<b>4.41 (3.65, 5.32)</b>	<b>4.09 (3.39, 4.93)</b>	<b>2.91 (2.52, 3.37)</b>	<b>2.63 (2.19, 3.15)</b>
Psychological	1.03 (0.98, 1.08)	1.68 (0.78, 3.6)	0.99 (0.72, 1.34)	<b>1.07 (1.01, 1.14)</b>	0.99 (0.91, 1.08)	0.93 (0.8, 1.07)	0.84 (0.64, 1.1)
Respiratory	0.99 (0.95, 1.04)	0.95 (0.81, 1.12)	0.77 (0.45, 1.32)	0.86 (0.68, 1.09)	1.01 (0.94, 1.09)	1.08 (0.92, 1.25)	1.06 (0.86, 1.31)
Asthma	1.02 (0.85, 1.23)	1.42 (0.84, 2.41)	0.77 (0.44, 1.33)	1.1 (0.83, 1.46)	0.84 (0.56, 1.25)	1.09 (0.66, 1.8)	1.47 (0.55, 3.93)
Emphysema/COPD	0.95 (0.77, 1.18)	1 (0.82, 1.22)	--	0.82 (0.1, 6.38)	0.87 (0.57, 1.33)	1.16 (0.88, 1.52)	<b>0.41 (0.18, 0.96)<sup>3</sup></b>

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ ); -- indicates too few cases available to calculate

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [221 cases on non-heat days, 17 cases on a heat day]

<sup>3</sup> While statistically significant, the estimate is based on a small number of cases [107 cases on non-heat days, 6 cases on a heat day]

Table 9.3: Relative risk analysis results for BLS data. Data presented as increased risk (95% CIs) of an EMS call on a 99th percentile (36.7 °C) heat day compared to a non-heat day. Data displayed by age category, and medical issue.<sup>1</sup>

Medical Issue	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
All Causes	<b>1.16 (1.13, 1.2)</b>	<b>1.22 (1.07, 1.39)</b>	0.91 (0.79, 1.05)	<b>1.19 (1.14, 1.25)</b>	<b>1.17 (1.11, 1.22)</b>	<b>1.15 (1.09, 1.21)</b>	<b>1.14 (1.07, 1.21)</b>
Trauma	<b>1.11 (1, 1.24)</b>	<b>1.33 (1.01, 1.79)</b>	0.84 (0.63, 1.13)	<b>1.16 (1.01, 1.33)</b>	1.06 (0.91, 1.23)	1.15 (0.97, 1.37)	1.07 (0.89, 1.29)
Non-Trauma	<b>1.16 (1.13, 1.2)</b>	<b>1.18 (1, 1.4)</b>	0.88 (0.71, 1.09)	<b>1.22 (1.16, 1.28)</b>	<b>1.17 (1.11, 1.23)</b>	<b>1.13 (1.06, 1.2)</b>	<b>1.13 (1.05, 1.22)</b>
Abdominal/Genito-Urinary	<b>1.1 (1.01, 1.19)</b>	0.94 (0.41, 2.13)	1.12 (0.63, 1.98)	<b>1.15 (1.01, 1.31)</b>	1.01 (0.88, 1.16)	1.07 (0.9, 1.28)	<b>1.26 (1.01, 1.57)</b>
Alcohol/Drugs	1.13 (1.02, 1.26)	1.03 (0.52, 2.01)	0.86 (0.36, 2.02)	1.13 (0.98, 1.3)	1.14 (0.95, 1.36)	1.12 (0.79, 1.6)	1.71 (0.93, 3.15)
Anaphylaxis/Allergy	1.14 (0.91, 1.44)	1.43 (0.8, 2.55)	0.83 (0.4, 1.72)	<b>1.4 (1.03, 1.91)</b>	0.99 (0.62, 1.58)	0.88 (0.45, 1.74)	0.78 (0.25, 2.43)
Cardiovascular	1.02 (0.94, 1.11)	0.94 (0.22, 4.02)	--	<b>1.39 (1.14, 1.7)</b>	1.04 (0.92, 1.19)	0.96 (0.84, 1.1)	0.91 (0.75, 1.11)
Metabolic/Endocrine	1.11 (0.98, 1.27)	1.2 (0.16, 8.93)	1.32 (0.32, 5.37)	1.16 (0.9, 1.5)	0.96 (0.76, 1.2)	1.14 (0.9, 1.44)	<b>1.69 (1.12, 2.54)</b>
Diabetes	1.08 (0.94, 1.25)	--	0.97 (0.13, 7.08)	1.2 (0.9, 1.59)	0.89 (0.68, 1.17)	1.19 (0.91, 1.55)	1.36 (0.79, 2.34)
Neurological	<b>1.07 (1, 1.14)</b>	1.09 (0.82, 1.45)	<b>0.41 (0.24, 0.72)<sup>2</sup></b>	<b>1.15 (1.03, 1.28)</b>	<b>1.12 (1, 1.25)</b>	1.07 (0.9, 1.14)	1.03 (0.89, 1.21)
Suspected CVA	0.99 (0.83, 1.18)	3.13 (0.35, 27.82)	--	1.61 (0.85, 3.04)	0.97 (0.68, 1.39)	0.95 (0.73, 1.24)	0.96 (0.7, 1.32)
Suspected TIA	0.42 (0.16, 1.08)	1 (0.65, 1.53)	1 (0.66, 1.53)	--	0.66 (0.15, 2.91)	0.55 (0.18, 1.66)	0.17 (0.02, 1.39)
Seizures	1.01 (0.89, 1.16)	0.8 (0.46, 1.4)	<b>0.35 (0.15, 0.79)<sup>3</sup></b>	1.06 (0.88, 1.27)	1.11 (0.89, 1.4)	0.97 (0.61, 1.56)	1.49 (0.75, 2.99)
Febrile Seizures	1.3 (0.93, 1.81)	1.38 (0.97, 1.96)	--	--	1.94 (0.27, 14.03)	--	1.94 (0.26, 14.38)
OBGYN	0.94 (0.72, 1.21)	1.1 (0.13, 9.04)	--	0.9 (0.69, 1.18)	<b>2.5 (1.09, 5.73)<sup>4</sup></b>	--	--
Other Medical	<b>1.43 (1.36, 1.51)</b>	<b>1.52 (1.14, 2.02)</b>	<b>1.61 (1.18, 2.21)</b>	<b>1.53 (1.39, 1.69)</b>	<b>1.44 (1.32, 1.57)</b>	<b>1.4 (1.27, 1.54)</b>	<b>1.3 (1.15, 1.47)</b>
Heat Illness & Dehydration	<b>6.68 (5.8, 7.71)</b>	<b>8.52 (3.94, 18)<sup>5</sup></b>	<b>6.06 (3.11, 11.8)</b>	<b>9.89 (7.97, 12)</b>	<b>9.07 (7.25, 11.35)</b>	<b>4.75 (3.8, 5.93)</b>	<b>4.31 (3.28, 5.67)</b>
Psychological	<b>1.11 (1.01, 1.22)</b>	1.99 (0.49, 8.08)	0.7 (0.32, 1.51)	1.1 (0.98, 1.25)	<b>1.19 (1.01, 1.41)</b>	1.07 (0.8, 1.43)	0.85 (0.48, 1.52)
Respiratory	1.07 (0.98, 1.17)	0.94 (0.66, 1.33)	0.77 (0.45, 1.32)	1.11 (0.91, 1.36)	1.11 (0.96, 1.29)	1.08 (0.92, 1.25)	1.06 (0.86, 1.31)
Asthma	0.92 (0.61, 1.39)	2.04 (0.82, 5.06)	0.78 (0.24, 2.55)	1.4 (0.82, 2.37)	0.15 (0.02, 1.1)	0.29 (0.04, 2.15)	1.41 (0.18, 10.72)
Emphysema/COPD	1.35 (0.91, 2)	1 (0.65, 1.53)	--	4.52, (0.58, 35)	0.88 (0.35, 2.2)	1.5 (0.91, 2.5)	1.5 (0.53, 4.21)

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ ); -- indicates too few cases available to calculate

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [1381 cases on non-heat days, 14 cases on a heat day]

<sup>3</sup> While statistically significant, the estimate is based on a small number of cases [702 cases on non-heat days, 6 cases on a heat day]

<sup>4</sup> While statistically significant, the estimate is based on a small number of cases [98 cases on non-heat days, 6 cases on a heat day]

<sup>5</sup> While statistically significant, the estimate is based on a small number of cases [43 cases on non-heat days, 9 cases on a heat day]

In the ALS data, only abdominal/genito-urinary, neurological, other medical, and heat illness and dehydration resulted in a statistically significant increase in risk of an EMS call on a 99<sup>th</sup> percentile heat day compared to a non heat day for all ages. 15-44 year olds are at increased risk for suspected CVA, suspected TIA, neurological, cardiovascular, and heat and dehydration; 45-64 were at increased risk for suspected TIA, other medical, and heat and dehydration; the 85+ age group was at increased risk of abdominal/genito-urinary, other medical, and heat and dehydration; and 65-84 years old were at increased risk for other medical and heat and dehydration. Please see table 9.4.

No statistically significant association was found in any of the three analyses for any age group for suspected CVA, seizures, febrile seizures, respiratory, and asthma health effects. Additionally, for the all ages group no association was found in any of the analyses for cardiovascular, psychological, OBGYN, and COPD health effects. 0-4 year olds also showed no statistically significant results from the ALS data analysis.

Protective associations were found for the BLS 95<sup>th</sup> percentile for suspected TIA of 0.6% (95% CIs: 0.42, 0.85) for all ages and of 0.57% (95% CIs: 0.34, 0.96) for the 85+ age group as well as for COPD of 0.41% (95% CIs: 0.18, 0.96) for 85+ age group. Both the BLS 99<sup>th</sup> percentile and the ALS analyses identified protective effects in the 5-14 year olds for neurological health effects of 0.41% (95% CIs: 0.24, 0.72) and 0.22% (95% CIs: 0.05, 0.86), respectively. This age group also has a protective effect of 0.35% (95% CIs: 0.15, 0.79) for seizures from the BLS 99<sup>th</sup> percentile analysis and of 0.61% (95% CIs: 0.38, 0.99) for non-trauma from the ALS analysis.

Table 9.4: Relative risk analysis results for ALS data. Data presented as increased risk (95% CIs) of an EMS call on a 99th percentile (36.7 °C) heat day compared to a non-heat day. Data displayed by age category, and medical issue.<sup>1</sup>

Medical Issue	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
All Causes	<b>1.14 (1.09, 1.2)</b>	1.09 (0.82, 1.45)	0.78 (0.55, 1.11)	<b>1.18 (1.08, 1.28)</b>	<b>1.2 (1.11, 1.29)</b>	1.09 (0.99, 1.19)	<b>1.13 (1, 1.26)</b>
Trauma	1.13 (0.91, 1.17)	1.47 (0.77, 2.79)	0.97 (0.46, 2.03)	1.17 (0.93, 1.47)	1.16 (0.83, 1.61)	0.87 (0.48, 1.55)	0.75 (0.28, 2)
Non-Trauma	<b>1.13 (1.07, 1.19)</b>	0.98 (0.7, 1.37)	<b>0.61 (0.38, 0.99)<sup>2</sup></b>	<b>1.13 (1.03, 1.25)</b>	<b>1.19 (1.1, 1.29)</b>	1.09 (0.99, 1.2)	<b>1.13 (1, 1.27)</b>
Abdominal/Genito-Urinary	<b>1.23 (1.05, 1.45)</b>	1.77 (0.23, 13.93)	1.51 (0.21, 10.81)	1.2 (0.82, 1.75)	1.05 (0.8, 1.38)	1.3 (0.97, 1.74)	<b>1.62 (1.13, 2.33)</b>
Alcohol/Drugs	1.04 (0.85, 1.28)	2.84 (0.88, 9.17)	--	0.89 (0.67, 1.18)	1.35 (0.99, 1.86)	0.83 (0.34, 2.05)	1.18 (0.28, 5.06)
Anaphylaxis/Allergy	1.06 (0.73, 1.54)	0.71 (0.17, 3.04)	0.7 (0.18, 2.73)	1.35 (0.81, 2.24)	1.16 (0.58, 2.31)	0.72 (0.19, 2.8)	--
Cardiovascular	1.02 (0.93, 1.12)	0.67 (0.09, 4.95)	--	<b>1.29 (1.01, 1.65)</b>	1.06 (0.93, 1.22)	0.97 (0.84, 1.12)	0.89 (0.72, 1.11)
Metabolic/Endocrine	1.14 (0.94, 1.39)	--	1.94 (0.27, 14.18)	1.07 (0.72, 1.57)	1.01 (0.72, 1.41)	1.29 (0.93, 1.79)	1.46 (0.76, 2.78)
Diabetes	1.12 (0.91, 1.38)	--	--	1.07 (0.72, 1.61)	1.03 (0.73, 1.46)	1.28 (0.9, 1.81)	1.19 (0.55, 2.56)
Neurological	<b>1.12 (1, 1.25)</b>	2.6 (0.81, 8.31)	<b>0.22 (0.05, 0.86)<sup>3</sup></b>	<b>1.23 (1, 1.51)</b>	1.1 (0.9, 1.35)	1.13 (0.91, 1.42)	1.11 (0.84, 1.47)
Suspected CVA	1.27 (0.93, 1.74)	1 (0.65, 1.53)	--	1.66 (0.4, 6.96)	0.92 (0.44, 1.93)	1.22 (0.73, 2.03)	1.61 (0.95, 2.73)
Suspected TIA	255 (0.92, 7.06)	1 (0.65, 1.53)	1 (0.66, 1.53)	<b>20 (1.9, 224)<sup>4</sup></b>	<b>11.67 (2.48, 54.82)<sup>5</sup></b>	1.32 (0.19, 8.97)	--
Seizure	0.99 (0.8, 1.23)	0.81 (0.36, 1.83)	0.3 (0.08, 1.2)	1.21 (0.9, 1.63)	1 (0.68, 1.48)	0.84 (0.4, 1.75)	0.63 (0.15, 3.62)
Febrile Seizure	1.01 (0.47, 2.18)	1.19 (0.55, 2.57)	--	--	--	--	--
OBGYN	1.14 (0.76, 1.7)	--	--	1.17 (0.79, 1.75)	2.4 (0.33, 17.57)	--	--
Other Medical	<b>1.39 (1.25, 1.53)</b>	0.97 (0.43, 2.22)	1.16 (0.45, 2.99)	1.15 (0.9, 1.48)	<b>1.48 (1.27, 1.73)</b>	<b>1.42 (1.19, 1.69)</b>	<b>1.45 (1.14, 1.86)</b>
Heat Illness & Dehydration	<b>7.07 (5.38, 9.3)</b>	8.15 (0.95, 69.65)	<b>10.2 (2.17, 47.89)<sup>6</sup></b>	<b>8.6 (4.7, 1)<sup>7</sup></b>	<b>7.21 (4.45, 11.67)</b>	<b>6.68 (4.36, 10)</b>	<b>5.97 (3.16, 11)</b>
Psychological	1.12 (0.9, 1.39)	6.79 (0.82, 56.32)	0.95 (0.12, 7.2)	1 (0.73, 1.38)	1.33 (0.95, 1.85)	0.76 (0.34, 1.7)	1.36 (0.51, 3.62)
Respiratory	1.03 (0.91, 1.17)	0.84 (0.44, 1.61)	0.78 (0.34, 1.79)	1.08 (0.79, 1.47)	1.19 (0.96, 1.47)	0.9 (0.72, 1.13)	1.09 (0.81, 1.47)
Asthma	1.3 (0.83, 2.03)	2.6 (0.81, 8.31)	--	1.59 (0.84, 3.04)	1 (0.31, 3.3)	1.15 (0.28, 4.73)	1.7 (0.24, 12.08)
Emphysema/COPD	1.38 (0.85, 2.23)	1 (0.65, 1.53)	--	5.81 (0.72, 47)	1.31 (0.54, 3.18)	1.38 (0.74, 2.6)	1.13 (0.27, 4.82)

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ ) ; -- indicates too few cases available to calculate

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [1137 cases on non-heat days, 17 cases on a heat day]

<sup>3</sup> While statistically significant, the estimate is based on a small number of cases [379 cases on non-heat days, 2 cases on a heat day]

<sup>4</sup> While statistically significant, the estimate is based on a small number of cases [2 cases on non-heat days, 1 cases on a heat day]

<sup>5</sup> While statistically significant, the estimate is based on a small number of cases [7 cases on non-heat days, 2 cases on a heat day]

<sup>6</sup> While statistically significant, the estimate is based on a small number of cases [8 cases on non-heat days, 2 cases on a heat day]

<sup>7</sup> While statistically significant, the estimate is based on a small number of cases [71 cases on non-heat days, 15 cases on a heat day]

## Transportation Outcomes

Significant relative risk values are in table 9.5 while changes in average call volumes can be found in table 9.6. All three analyses identified significant increases in calls resulting in no transportation and BLS transportation for all ages; no transportation, ALS transportation, and other transportation for 15-44 year olds; and BLS transportation for 45-64 year olds as well as 65-84 year olds. Additionally, both BLS analyses identified significant results for all other age groups except the 5-14 year olds in no transportation, 0-4 year olds as well as 15-44 year olds in BLS transportation, and 65-84 year olds in other transportation. The 95<sup>th</sup> percentile analyses also identified significant results for all ages in other transportation. The ALS analysis identified significant results for 85+ in BLS transportation and all ages and 45-64 year olds in ALS transportation.

		No Transportation	BLS Transportation	ALS Transportation	Other Transportation
Table 9.5: Relative risk analysis results for BLS and ALS data. Data presented as increased risk (95% CIs) of an EMS call on a 95th percentile (29.7 °C) or a 99th percentile (36.7 °C) heat day compared to a non-heat day. Data displayed by age category for all transportation categories.					
All Ages	BLS 95th	<b>1.12 (1.09, 1.15)</b>	<b>1.07 (1.05, 1.09)</b>	1.02 (0.99, 1.06)	<b>1.08 (1.03, 1.13)</b>
	BLS 99th	<b>1.22 (1.16, 1.28)</b>	<b>1.14 (1.1, 1.19)</b>	<b>1.09 (1.02, 1.17)</b>	1.09 (0.99, 1.19)
	ALS 99th	<b>1.2 (1.07, 1.35)</b>	<b>1.18 (1.1, 1.27)</b>	<b>1.1 (1.03, 1.18)</b>	1.06 (0.81, 1.39)
0-4	BLS 95th	<b>1.2 (1.09, 1.32)</b>	<b>1.16 (1.05, 1.29)</b>	1.05 (0.86, 1.28)	1.05 (0.91, 1.21)
	BLS 99th	<b>1.23 (1.02, 1.49)</b>	<b>1.37 (1.12, 1.67)</b>	1.03 (0.68, 1.58)	1.09 (0.81, 1.46)
	ALS 99th	1.46 (0.8, 2.68)	1.21 (0.75, 1.96)	1.06 (0.7, 1.59)	0.36 (0.9, 1.46)
5-14	BLS 95th	1.08 (0.98, 1.18)	1.06 (0.96, 1.16)	1.05 (0.83, 1.31)	1.06 (0.92, 1.22)
	BLS 99th	0.98 (0.79, 1.21)	0.86 (0.69, 1.07)	1.05 (0.65, 1.7)	0.81 (0.57, 1.14)
	ALS 99th	0.5 (0.18, 1.38)	0.87 (0.47, 1.63)	0.95 (0.58, 1.57)	0.31 (0.4, 2.33)
15-44	BLS 95th	<b>1.14 (1.1, 1.19)</b>	<b>1.09 (1.07, 1.12)</b>	<b>1.06 (1, 1.14)</b>	<b>1.08 (1.01, 1.16)</b>
	BLS 99th	<b>1.26 (1.16, 1.36)</b>	<b>1.16 (1.09, 1.22)</b>	<b>1.2 (1.06, 1.37)</b>	<b>1.16 (1.01, 1.33)</b>
	ALS 99th	<b>1.32 (1.08, 1.62)</b>	1.05 (0.91, 1.2)	<b>1.21 (1.06, 1.38)</b>	<b>1.54 (1.03, 2.3)</b>
45-64	BLS 95th	<b>1.12 (1.07, 1.17)</b>	<b>1.08 (1.05, 1.11)</b>	1.04 (0.98, 1.1)	<b>1.09 (1, 1.19)</b>
	BLS 99th	<b>1.26 (1.15, 1.37)</b>	<b>1.14 (1.08, 1.21)</b>	<b>1.14 (1.02, 1.28)</b>	0.92 (0.75, 1.12)
	ALS 99th	1.26 (1.04, 1.53)	<b>1.23 (1.1, 1.37)</b>	<b>1.17 (1.05, 1.31)</b>	1.14 (0.7, 1.84)
65-84	BLS 95th	<b>1.1 (1.05, 1.15)</b>	<b>1.04 (1.01, 1.08)</b>	1 (0.94, 1.06)	<b>1.11 (1, 1.23)</b>
	BLS 99th	<b>1.18 (1.07, 1.31)</b>	<b>1.14 (1.08, 1.21)</b>	1.04 (0.92, 1.18)	<b>1.31 (1.06, 1.61)</b>
	ALS 99th	1.06 (0.83, 1.36)	<b>1.19 (1.05, 1.35)</b>	1.04 (0.93, 1.18)	0.48 (0.19, 1.21)
85+	BLS 95th	<b>1.07 (1, 1.14)</b>	1.01 (0.97, 1.05)	0.98 (0.9, 1.07)	1.01 (0.85, 1.2)
	BLS 99th	<b>1.19 (1.04, 1.35)</b>	<b>1.16 (1.07, 1.25)</b>	0.91 (0.76, 1.1)	1.16 (0.82, 1.63)
	ALS 99th	1.13 (0.81, 1.59)	<b>1.35 (1.15, 1.59)</b>	0.89 (0.74, 1.59)	1.75 (0.83, 3.68)

Table 9.6: Call counts for transportation outcomes for BLS and ALS data. Data presented as the change in average EMS call volumes ( $\Delta V$ ) on a 95th percentile (29.7 °C) or a 99th percentile (36.7 °C) heat day compared to a non-heat day by age category. Data displayed by age category for all transportation categories.

		No Transportation			BLS Transportation			ALS Transportation			Other Transportation		
		NHD	HD	$\Delta V$	NHD	HD	$\Delta V$	NHD	HD	$\Delta V$	NHD	HD	$\Delta V$
All Ages	BLS 95th	<b>93.6</b>	<b>105.0</b>	<b>11.4</b>	<b>220.0</b>	<b>235.0</b>	<b>15.0</b>	45.5	46.5	1.0	<b>23.5</b>	<b>25.3</b>	<b>1.8</b>
	BLS 99th	<b>94.5</b>	<b>115.0</b>	<b>20.5</b>	<b>221.0</b>	<b>253.0</b>	<b>32.0</b>	<b>45.6</b>	<b>49.8</b>	<b>4.2</b>	23.6	25.7	2.1
	ALS 99th	<b>13.0</b>	<b>15.6</b>	<b>2.6</b>	<b>39.5</b>	<b>46.7</b>	<b>7.2</b>	<b>46.5</b>	<b>51.1</b>	<b>4.6</b>	2.6	2.8	0.2
0-4	BLS 95th	<b>4.3</b>	<b>5.1</b>	<b>0.8</b>	<b>3.6</b>	<b>4.2</b>	<b>0.6</b>	1.0	1.0	0.0	2.0	2.1	0.1
	BLS 99th	<b>4.4</b>	<b>5.4</b>	<b>1.0</b>	<b>3.7</b>	<b>5.0</b>	<b>1.3</b>	1.0	1.0	0.0	2.0	2.2	0.2
	ALS 99th	0.3	0.5	0.2	0.7	0.9	0.2	1.0	1.1	0.1	0.3	0.1	-0.2
5-14	BLS 95th	4.4	4.7	0.3	4.9	5.2	0.3	0.7	0.7	0.0	2.1	2.2	0.1
	BLS 99th	4.4	4.3	-0.1	5.0	4.3	-0.7	0.7	0.7	0.0	2.1	1.7	-0.4
	ALS 99th	0.4	0.2	-0.2	0.6	0.5	-0.1	0.7	0.7	0.0	0.1	0.0	-0.1
15-44	BLS 95th	<b>33.3</b>	<b>38.2</b>	<b>4.9</b>	<b>69.8</b>	<b>76.5</b>	<b>6.7</b>	<b>10.2</b>	<b>10.8</b>	<b>0.6</b>	<b>9.6</b>	<b>10.4</b>	<b>0.8</b>
	BLS 99th	<b>33.7</b>	<b>42.4</b>	<b>8.7</b>	<b>70.4</b>	<b>81.4</b>	<b>11.0</b>	<b>10.2</b>	<b>12.3</b>	<b>2.1</b>	<b>9.6</b>	<b>11.1</b>	<b>1.5</b>
	ALS 99th	<b>3.7</b>	<b>4.8</b>	<b>1.2</b>	10.1	10.5	0.4	<b>10.4</b>	<b>12.6</b>	<b>2.2</b>	<b>0.8</b>	<b>1.2</b>	<b>0.4</b>
45-64	BLS 95th	<b>23.0</b>	<b>25.6</b>	<b>2.6</b>	<b>61.7</b>	<b>66.7</b>	<b>5.0</b>	14.7	15.2	0.5	<b>5.2</b>	<b>5.7</b>	<b>0.5</b>
	BLS 99th	<b>23.2</b>	<b>29.1</b>	<b>5.9</b>	<b>62.1</b>	<b>70.8</b>	<b>8.7</b>	<b>14.7</b>	<b>16.7</b>	<b>2.0</b>	5.3	4.9	-0.4
	ALS 99th	4.2	5.3	1.1	12.7	15.5	2.8	<b>15.0</b>	<b>17.5</b>	<b>2.5</b>	0.8	0.9	0.1
65-84	BLS 95th	<b>18.6</b>	<b>20.2</b>	<b>1.6</b>	<b>50.1</b>	<b>52.0</b>	<b>1.9</b>	13.4	13.3	-0.1	<b>3.3</b>	<b>3.6</b>	<b>0.3</b>
	BLS 99th	<b>18.7</b>	<b>22.0</b>	<b>3.3</b>	<b>50.2</b>	<b>57.1</b>	<b>6.9</b>	13.4	13.9	0.5	<b>3.3</b>	<b>4.3</b>	<b>1.0</b>
	ALS 99th	3.1	3.2	0.2	<b>10.2</b>	<b>12.1</b>	<b>1.9</b>	13.6	14.1	0.5	0.5	0.2	-0.3
85+	BLS 95th	<b>10.1</b>	<b>10.7</b>	<b>0.6</b>	29.9	30.0	0.1	5.7	5.5	-0.1	1.3	1.3	0.0
	BLS 99th	<b>10.1</b>	<b>12.0</b>	<b>1.9</b>	<b>29.8</b>	<b>34.4</b>	<b>4.6</b>	5.7	5.1	-0.5	1.3	1.5	0.2
	ALS 99th	1.5	1.6	0.2	<b>5.3</b>	<b>7.1</b>	<b>1.8</b>	5.7	5.1	-0.6	0.2	0.4	0.2

## Study Power

The six-year study timeframe included a total of 918 days with an average number of calls per day of 393.7 and 103 for BLS and ALS data, respectively. The sensitivity analysis for the removal of missing age and gender data demonstrated that removal of this data did not significantly impact the data for all ages and all causes given the two-sided p-value of 0.9928. However, both BLS and ALS data were weakened by diminished study power in many of the age categories and specific non-trauma cases, with many of the causes in the ALS data having less than 20 calls on all heat days combined (see table 9.8).

Table 9.7: Total call counts for EMS BLS calls from the relative risk analysis results. Counts presented for heat days (HD) at or above the 95th percentile (29.7 °C) compared to non-heat days (NHD), by age group, medical issue, and level of transportation)<sup>1</sup>

Medical Issue	All Ages		0-4		5-14		15-44		45-64		65-84		85+	
	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD
All Causes	315251	46183	9039	1397	9968	1446	101320	15267	86133	12744	70238	9983	38553	5346
Trauma	40764	6241	1601	293	2671	402	16728	2639	9112	1386	6366	960	4286	561
Non-Trauma	208056	29989	5316	786	4427	626	60681	9013	61064	8897	50986	7132	25582	3533
Abdominal/Genito-Urinary	23186	3266	230	36	382	65	7768	1101	6887	1000	5246	695	2671	369
Alcohol/Drugs	15127	2226	318	48	254	37	8531	1230	4768	734	1021	139	235	38
Anaphylaxis/Allergy	3044	471	326	57	357	45	1099	160	759	127	365	61	138	21
Cardiovascular	26730	3529	73	16	81	<b>5</b>	2903	390	9210	1293	9888	1245	4575	580
Metabolic/Endocrine	8204	1235	30	<b>5</b>	55	<b>9</b>	2040	271	2988	465	2542	405	549	80
Diabetes	6169	906	<b>19</b>	<b>2</b>	37	<b>6</b>	1555	195	2277	353	1898	298	383	52
Neurological	42106	5880	1548	210	1230	165	11997	1728	11060	1545	10426	1444	5845	788
Suspected CVA	5685	474	<b>13</b>	<b>1</b>	<b>5</b>	<b>0</b>	226	37	1257	171	2484	327	1700	221
Suspected TIA	642	52	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	30	<b>0</b>	115	<b>11</b>	276	24	221	<b>17</b>
Seizures	9632	1324	587	87	626	82	4644	650	2777	388	771	89	227	28
Febrile Seizures	917	120	808	105	43	<b>7</b>	22	<b>2</b>	<b>18</b>	<b>4</b>	<b>5</b>	<b>1</b>	21	<b>1</b>
OBGYN	2494	360	34	<b>4</b>	<b>11</b>	<b>1</b>	2292	334	90	<b>14</b>	28	<b>2</b>	39	<b>5</b>
Other Medical	50200	7964	1383	229	964	165	11961	2020	14809	2291	13346	2085	7737	1174
Heat Illness & Dehydration	2319	1081	34	18	54	31	470	282	467	259	800	315	494	176
Psychological	15928	2221	35	<b>8</b>	366	49	8525	1248	4794	646	1639	205	569	65
Respiratory	21037	2837	1339	173	725	85	3565	531	5699	782	6485853	853	25582	3533
Asthma	992	138	88	17	144	<b>15</b>	367	55	246	28	122	<b>18</b>	<b>15</b>	<b>5</b>
Emphysema/COPD	719	93	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>9</b>	<b>1</b>	212	25	390	61	107	<b>6</b>
<b>Level of Transport</b>														
No Transportation	75668	11506	3456	563	3530	516	26945	4201	18613	2820	15003	2226	8121	1180
BLS Transport	177873	25806	2930	462	3981	571	56432	8413	49864	7332	40516	5723	24150	3305
ALS Transport	36800	5119	777	111	556	79	8209	1189	11856	1675	10836	1459	4566	606
Other Transport	18975	2779	1645	234	1671	240	7738	1139	4228	626	2640	396	1053	144

<sup>1</sup> Bolded values are counts less than 20.

Table 9.8: Total call counts for EMS BLS calls from the relative risk analysis results. Counts presented for heat days (HD) at or above the 99th percentile (36.7 °C) compared to non-heat days (NHD), by age group, medical issue, and level of transportation).<sup>1</sup>

Medical Issue	All Ages		0-4		5-14		15-44		45-64		65-84		85+	
	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD
All Causes	351428	10006	10132	304	11166	248	113266	3321	96132	2745	78028	2193	42704	1195
Trauma	45757	1248	1834	60	3011	62	18830	537	10233	265	7126	200	4723	124
Non-Trauma	231438	6607	5930	172	4946	107	67664	2030	68009	1952	56561	1559	28328	787
Abdominal/Genito-Urinary	25757	695	260	<b>6</b>	437	<b>12</b>	8625	244	7697	190	5789	152	2949	91
Alcohol/Drugs	16884	469	357	<b>9</b>	285	<b>6</b>	9498	263	5353	149	1129	31	262	<b>11</b>
Anaphylaxis/Allergy	3419	96	370	<b>13</b>	394	<b>8</b>	1217	42	865	21	417	<b>9</b>	156	<b>3</b>
Cardiovascular	29518	741	87	<b>2</b>	86	<b>0</b>	3184	109	10241	262	10878	255	5042	133
Metabolic/Endocrine	9188	251	34	<b>1</b>	62	<b>2</b>	2247	64	3374	79	2867	80	604	25
Diabetes	6892	183	21	<b>0</b>	42	<b>1</b>	1700	50	2574	56	2134	62	421	<b>14</b>
Neurological	46762	1224	1712	46	1381	<b>14</b>	13349	376	12268	337	11583	287	6469	164
Suspected CVA	6280	152	<b>13</b>	<b>1</b>	<b>5</b>	<b>0</b>	253	<b>10</b>	1385	33	2747	64	1877	44
Suspected TIA	687	<b>7</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>30</b>	<b>0</b>	124	<b>2</b>	296	<b>4</b>	237	<b>1</b>
Seizures	10690	266	661	<b>13</b>	702	<b>6</b>	5160	134	3081	84	840	20	246	<b>9</b>
Febrile Seizures	1005	32	883	30	50	<b>0</b>	24	<b>0</b>	21	<b>1</b>	<b>6</b>	<b>0</b>	21	<b>1</b>
OBGYN	2790	64	37	<b>1</b>	<b>12</b>	<b>0</b>	2569	57	98	<b>6</b>	39	<b>0</b>	44	<b>0</b>
Other Medical	56188	1976	1554	58	1086	43	13473	508	16518	582	14921	510	8636	275
Heat Illness & Dehydration	2921	479	43	<b>9</b>	74	<b>11</b>	605	147	594	132	999	116	606	64
Psychological	17668	481	41	<b>2</b>	408	<b>7</b>	9515	258	5286	154	1797	47	<b>621</b>	<b>13</b>
Respiratory	23264	610	1478	34	795	<b>15</b>	3987	109	6309	172	7150	188	3545	92
Asthma	1105	25	100	<b>5</b>	156	<b>3</b>	408	<b>14</b>	273	<b>1</b>	139	<b>1</b>	29	<b>1</b>
Emphysema/COPD	786	26	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>9</b>	<b>1</b>	232	51	435	<b>16</b>	109	<b>4</b>
<b>Level of Transport</b>														
No Transportation	84641	2533	3901	118	3951	95	30213	933	20793	640	16745	484	9038	263
BLS Transport	198115	5564	3282	110	4458	94	63055	1790	55639	1557	44982	1257	26699	756
ALS Transport	40824	1095	866	22	619	<b>16</b>	9128	270	13163	368	11989	306	5059	113
Other Transport	21189	565	1830	49	1874	37	8632	245	4747	107	2942	94	1164	33

<sup>1</sup> Bolded values are counts less than 20.

Table 9.9: Total call counts for EMS ALS calls from the relative risk analysis results. Counts presented for heat days (HD) at or above the 99th percentile (36.7 °C) compared to non-heat days (NHD), by age group, medical issue, and level of transportation.<sup>1</sup>

Medical Issue	All Ages		0-4		5-14		15-44		45-64		65-84		85+	
	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD	NHD	HD
All Causes	91987	2578	2085	56	1623	31	22543	651	29558	868	24750	657	11428	315
Trauma	5962	165	277	<b>10</b>	295	<b>7</b>	3158	91	1446	41	567	<b>12</b>	219	<b>4</b>
Non-Trauma	80021	2211	1622	39	1136	<b>17</b>	17034	474	26346	767	23161	617	10722	297
Abdominal/Genito-Urinary	5020	152	23	<b>1</b>	27	<b>1</b>	882	26	1908	49	1476	47	704	28
Alcohol/Drugs	4147	106	43	<b>3</b>	43	<b>0</b>	2509	55	1237	41	246	<b>5</b>	69	<b>2</b>
Anaphylaxis/Allergy	1116	29	115	<b>2</b>	116	<b>2</b>	423	<b>14</b>	316	<b>9</b>	113	<b>2</b>	33	<b>0</b>
Cardiovascular	23543	587	61	<b>1</b>	53	<b>0</b>	2269	72	8404	219	8822	209	3934	86
Metabolic/Endocrine	4169	117	<b>14</b>	<b>0</b>	21	<b>1</b>	992	26	1501	37	1361	43	280	<b>10</b>
Diabetes	3738	103	<b>7</b>	<b>0</b>	<b>17</b>	<b>0</b>	909	24	1348	34	1217	38	240	<b>7</b>
Neurological	13190	361	593	<b>15</b>	379	<b>2</b>	3472	105	3558	96	3284	91	1904	52
Suspected CVA	1313	41	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	49	<b>2</b>	310	<b>7</b>	572	<b>17</b>	381	<b>15</b>
Suspected TIA	64	<b>4</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>2</b>	<b>1</b>	<b>7</b>	<b>2</b>	<b>31</b>	<b>1</b>	24	<b>0</b>
Seizures	3736	91	301	<b>6</b>	268	<b>2</b>	1547	46	1101	27	389	<b>8</b>	130	<b>2</b>
Febrile Seizures	282	<b>7</b>	240	<b>7</b>	<b>14</b>	<b>0</b>	<b>7</b>	<b>0</b>	<b>6</b>	<b>0</b>	<b>3</b>	<b>0</b>	<b>12</b>	<b>0</b>
OBGYN	965	27	30	<b>0</b>	<b>1</b>	<b>0</b>	902	26	<b>17</b>	<b>1</b>	<b>3</b>	<b>0</b>	<b>12</b>	<b>0</b>
Other Medical	13853	471	251	<b>6</b>	141	<b>4</b>	2509	55	1237	41	246	5	69	2
Heat Illness & Dehydration	438	76	<b>5</b>	<b>1</b>	<b>8</b>	<b>2</b>	<b>71</b>	<b>15</b>	119	21	153	25	82	<b>12</b>
Psychological	3180	87	<b>6</b>	<b>1</b>	43	<b>1</b>	1580	39	1109	36	322	6	120	4
Respiratory	10838	274	486	<b>10</b>	312	<b>6</b>	1467	39	3088	90	3731	82	1754	47
Asthma	565	<b>18</b>	47	<b>3</b>	71	<b>0</b>	230	<b>9</b>	122	<b>3</b>	71	<b>2</b>	24	<b>1</b>
Emphysema/COPD	561	<b>19</b>	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>7</b>	<b>1</b>	156	<b>5</b>	71	<b>2</b>	24	<b>1</b>
<b>Level of Transport</b>														
No Transportation	11672	344	306	<b>11</b>	324	<b>4</b>	3269	106	3747	116	2730	71	1296	36
BLS Transport	35417	1027	638	19	513	<b>11</b>	9018	232	11368	342	9175	267	4705	156
ALS Transport	41620	1124	887	23	641	<b>15</b>	9323	277	13457	386	12178	311	5134	112
Other Transport	2343	61	226	<b>2</b>	133	<b>1</b>	688	26	682	19	427	<b>5</b>	187	<b>8</b>

<sup>1</sup> Bolded values are counts less than 20.

Table 9.10: Average daily counts of EMS calls from the relative risk analysis results for BLS and ALS data. Counts presented for heat days (HD) at or above the 95th percentile (29.7 °C) for BLS data, 99th percentile for BLS data, and 99th percentile for ALS data compared to non-heat days (NHD), by medical issue and level of transportation). The difference in call counts from a NDHs to HDs is also presented.

Medical Issue	BLS 95th %ile All Ages			BLS 99th %ile All Ages			ALS 99th %ile All Ages		
	NHD	HD	Diff.	NHD	HD	Diff	NHD	HD	Diff
All Causes	390.0	420.0	30	392.0	455.0	63	103.0	117.0	14
Trauma	50.5	56.7	6	51.1	56.7	6	6.7	7.5	1
Non-Trauma	257.0	273.0	16	258.0	300.0	42	89.3	100.0	11
Abdominal/Genito-Urinary	28.7	29.7	1	28.7	31.6	3	5.6	6.9	1
Alcohol/Drugs	18.7	20.2	2	18.8	21.3	3	4.6	4.8	0
Anaphylaxis/Allergy	3.8	4.3	1	3.8	4.4	1	1.3	1.3	0
Cardiovascular	33.1	32.1	-1	32.9	33.7	1	26.3	26.7	0
Metabolic/Endocrine	10.2	11.2	1	10.3	11.4	1	4.7	5.3	1
Diabetes	7.6	8.2	1	7.7	8.3	1	4.2	4.7	1
Neurological	52.1	53.5	1	52.2	55.6	3	14.7	16.4	2
Suspected CVA	7.0	6.8	0	7.0	6.9	0	1.5	1.9	0
Suspected TIA	0.8	0.5	0	0.8	0.3	0	0.1	0.2	0
Seizure	11.9	12.0	0	11.9	12.1	0	4.2	4.1	0
Febrile Seizure	1.1	1.1	0	1.1	1.5	0	0.3	0.3	0
OBGYN	3.1	3.3	0	3.1	2.9	0	1.1	1.2	0
Other Medical	62.1	72.4	10	62.7	89.8	27	15.5	21.4	6
Heat Illness & Dehydration	2.9	9.8	7	3.3	21.8	19	0.4	1.5	1
Psychological	19.7	20.2	1	19.7	21.9	2	3.6	4.0	0
Respiratory	26.0	25.8	0	26.0	27.7	2	12.1	12.5	0
Asthma	1.2	1.3	0	1.2	1.1	0	0.6	0.8	0
Emphysema/COPD	0.9	0.8	0	0.9	1.2	0	0.6	0.9	0
<b>Level of Transport</b>									
No Transportation	93.6	105.0	11	94.5	115.0	21	13.0	15.6	3
BLS Transport	220.0	235.0	15	221.0	253.0	32	39.5	46.7	7
ALS Transport	45.5	46.5	1	45.6	49.8	4	46.5	51.1	5
Other Transport	23.5	25.3	2	23.6	25.7	2	2.6	2.8	0

Table 9.11: Statistically significant duration and cool down effects on relative risk association for BLS data at the 95th percentile (29.7 °C).

Characteristic	All causes	Estimate	Std. Error	t value	Pr(> t )
Duration	Intercept	-8.4496	0.0134	-630.93	<2e-16
	Slope	0.0097	0.0043	2.25	0.0264
Cool Down	Intercept	-8.7270	0.0679	-128.50	<2e-16
	Slope	0.0135	0.0030	4.48	1.870E-05

### Sensitivity Analysis

The sensitivity analysis shows that removal of missing age and gender data does not seem to have significantly impacted the data for all ages and all causes given the two-sided p-value of 0.9928. Please see table 8.

Table 9.12: Sensitivity analysis for removal of missing age and gender data from EMS BLS data at the 95th percentile of humidex.

Data (Threshold)	All causes	N - calls in summer time frame (all ages, all causes)	Standard Deviation	Standard Error	Z score	two-tailed pvalue
BLS Calls 2007-2012 including missing (29.7°C)	1.09% (1.07%, 1.11%)	441119	3.795	0.006		
BLS Calls 2007-2012 excluding missing (29.7°C)	1.08% (0.61%, 4.61%)	361434	6.135	0.010	-0.009	<b>0.9928</b>

## **APPENDIX 10:**

### **RESULTS—TIME-SERIES ANALYSIS**

The time-series (TS) analysis results presented below includes BLS data with a humidex threshold at the 95<sup>th</sup> percentile (29.7 °C) and ALS data with a humidex threshold at the 99<sup>th</sup> percentile (36.7 °C). For this analysis, no difference was seen in the results of the BLS data at the 95<sup>th</sup> and the 99<sup>th</sup> percentiles, so only those run as the 95<sup>th</sup> are present. All time-series results are presented by age category for medical issue and level of transportation. Additionally, results for the analyses of the effects of extreme heat characteristics in included.

#### List Of Tables:

10.1—Time series analysis result for BLS data for health outcomes

10.2—Time series analysis results for ALS data for health outcomes

10.3—Time series analysis results for BLS and ALS data for transportation

#### **Health Outcomes**

BLS and ALS analyses both contain statistically significant increases in EMS calls for every 1 degree increase above their respective threshold (40.7 °C) for BLS and 39.7 °C) for ALS data) for all causes, all ages; 6.6% (95% CIs: 4.5%, 8.7%) for BLS and 3.8% (95% CIs: 1.1%, 6.5%) for ALS. Additionally, both analyses identified significant results for all causes in 45-64 year olds; non-trauma in the all ages category; other medical for all ages, 15-44, 45-64, and 65-84 age groups; heat and dehydration in all ages, 15-44, 45-64, 65-84, and 85+ age groups; and emphysema/COPD in the 15-44 age group. The only additional statistically significant result for the ALS data was for OBGYN in the 45-64 age group. Please see Tables 10.1 and 10.2.

Significant results in the BLS data only included all causes for all age groups; non trauma for all age groups excluding 0-4; metabolic for the 0-4 and 5-14 age groups; diabetes for the 15-44 age group; neurological for the 45-64 age group; suspected TIA for the 64-85 age group;

febrile seizures for the 0-4 age group; other medical for the 0-4, 5-14, and 85+ age groups; psychological for all ages and the 5-14 and 45-64 age groups; and asthma for the 15-44 age group. The only cause producing a protective effect in this analysis is trauma in the 15-44 age group. The causes with the most significant results are other medical (7), followed by all causes (6), and non trauma (5) and heat and dehydration (5). The age groups with the most significant results included 15-44 year olds (8), followed by all ages (6), 45-64 (5) and 65-84 (5), and 0-4 (4), 5-14 (4), and 85+ (4). Please see table 10.1.

### **Transportation Outcomes**

Transportation outcomes showed an increase in no transportation above the respective thresholds for the BLS and ALS data with both analyses producing significant results for all ages and the 15-44 and 45-64 age groups. BLS data identified significant results for no transportation in all but the 85+ age group. BLS transportation also showed increases in both analyses with all ages and the 45-64 and 65-84 age groups producing positive results. Additionally, the BLS data had significant results for BLS transportation in the 15-44 and 85+ age groups. ALS data identified significant results for other transportation in the 85+ age group as well.

### **Study Power**

The time series analysis was considerably limited by study power. Due to the extremely high optimal threshold of 40.7 for the BLS data and 39.7 for the ALS data, the timeframe contained only 5 days above the threshold for the BLS data and 8 days above the threshold for ALS data. Combined with the lower number of daily calls in the ALS dataset compared to the BLS data set, the ALS analysis is particularly affected by study power, leaving only the most

inclusive or greatest impact categories with enough calls to support the analysis. Statistically significant results with total call counts lower than 20 are reflected in Tables 4 and 5.

Table 10.1: Time-series analysis results for BLS data. Percent changes in daily EMS calls presented for every 1 degree increase above 40.7 °C humidex (95 CIs). Data displayed by age category, medical issue, and level of transport.<sup>1</sup>

Medical Issue	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
All Causes	<b>6.6 (4.5, 8.7)</b>	<b>12 (1.7, 22)</b>	4.7 (-5.5, 16)	<b>5.1 (1.9, 8.3)</b>	<b>8.6 (5.3, 12)</b>	<b>7.6 (3.7, 12)</b>	<b>8.1 (2.9, 14)</b>
Trauma	-4.3 (-10, 2.0)	3.4 (-17, 29)	15 (-34, 11)	<b>-12 (-20, -2.6)</b>	-2.9 (-13, 8.5)	4.5 (-7.1, 18)	7.0 (-8.1, 25)
Non-Trauma	<b>10 (7.6, 13)</b>	-0.5 (-100, Inf)	<b>7.9 (4.5, 12)</b>	<b>11 (6.2, 16)</b>	-0.5 (-100, Inf)	<b>7.9 (4.5, 12)</b>	<b>11 (6.2, 156)</b>
Abdo/Genito-Urinary	3.9 (-2.5, 11)	40 (-3.1, 103)	-60 (-95, 195)	7.6 (-2.6, 19)	4.0 (-6.9, 16)	2.7 (-10, 18)	-5.4 (-23, 16)
Alcohol/Drugs	-3.3 (-12, 5.7)	-0.3 (-43, 75)	--	-0.4 (-11, 11)	-4.5 (-18, 12)	-34 (-67, 32)	3.3 (-43, 88)
Anaphylaxis/Allergy	-13 (-30, 9.1)	-89 (-100, 2021)	-11 (-54, 71)	-17 (-44, 24)	-23 (-53, 27)	13 (-23, 68)	31 (-26, 130)
Cardiovascular	2.5 (-4.2, 9.6)	--	--	16 (-0.1, 34)	4.9 (-4.7, 16)	-3.1 (-13, 8.6)	-2.2 (-17, 15)
Metabolic/Endocrine	2.3 (-7.1, 13)	<b>91 (7.6, 240)<sup>2</sup></b>	<b>96 (13, 240)<sup>3</sup></b>	16 (-1.6, 36)	-1.6 (-17, 17)	-11 (-29, 11)	-7.1 (-39, 41)
Diabetes	1.9 (-8.8, 149)	--	--	<b>22 (2.8, 45)<sup>4</sup></b>	-6.5 (-25, 16)	-1.5 (-21, 23)	-90 (-100, 2062)
Neurological	<b>5.9 (1, 11)</b>	14 (-6.7, 40)	7.5 (-18, 41)	1.1 (-7.3, 10)	<b>11 (2.9, 20)</b>	5.0 (-4.1, 15)	3.3 (-8.9, 17)
Suspected CVA	8.7 (-4.2, 23)	--	--	13 (-35, 97)	-2.4 (-29, 33)	15 (-2.8, 37)	5.0 (-18, 34)
Suspected TIA	24 (-18, 89)	15 (-100, Inf)	15 (-100, Inf)	--	18 (-52, 187)	<b>49 (4.7, 112)<sup>5</sup></b>	--
Seizure	-3.7 (-14, 8.1)	-9.7 (-45, 49)	5.6 (-30, 59)	-6.9 (-21, 10)	3.2 (-14, 24)	-7.6 (-42, 47)	--
Febrile Seizure	20 (-2.2, 48)	<b>25 (0.8, 55)<sup>6</sup></b>	--	--	--	--	--
OBGYN	2.9 (-16, 25)	--	--	1.3 (-18, 25)	41 (-19, 146.)	--	--
Other Medical	<b>24 (20, 27)</b>	<b>31 (12, 54)<sup>7</sup></b>	<b>3.3 (22, 69)<sup>8</sup></b>	<b>25 (18, 33)</b>	<b>21 (14, 28)</b>	<b>22 (15, 307)</b>	<b>23 (14, 33)</b>
Heat & Dehydration	<b>49 (40, 58)</b>	49 (-4, 132)	34 (-4.8, 88)	<b>48 (34, 63)</b>	<b>46 (31, 62)</b>	<b>42 (27.8, 58)</b>	<b>59 (40, 81)</b>
Psychological	<b>12 (4.1, 19)</b>	--	<b>43 (1.9, 100)<sup>9</sup></b>	6.6 (-3.3, 17)	<b>16 (3.3, 30)</b>	12 (-11, 40)	27 (-6.5, 73)
Respiratory	3.1 (-3.7, 10)	-0.5 (-25, 32)	-8.2 (-44, 48)	12 (-2.1, 286)	0.7 (-128, 15)	-3.1 (-16, 11)	9.2 (-6.8, 28)
Asthma	9.4 (-17, 44)	--	-54 (-98, 1130)	<b>39 (6.0, 82)<sup>10</sup></b>	--	--	--
Emphysema/COPD	14. (-15, 54)	-3.9 (-100, Inf)	--	<b>130 (23, 328)<sup>11</sup></b>	19 (-26, 92)	-47 (-84, 71)	83 (19, 183)

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ ); -- indicates too few cases available to calculate

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [34 cases on non-heat days, 1 cases on a heat day]

<sup>3</sup> While statistically significant, the estimate is based on a small number of cases [63 cases on non-heat days, 1 cases on a heat day]

<sup>4</sup> While statistically significant, the estimate is based on a small number of cases [1734 cases on non-heat days, 16 cases on a heat day]

<sup>5</sup> While statistically significant, the estimate is based on a small number of cases [299 cases on non-heat days, 1 cases on a heat day]

<sup>6</sup> While statistically significant, the estimate is based on a small number of cases [905 cases on non-heat days, 8 cases on a heat day]

<sup>7</sup> While statistically significant, the estimate is based on a small number of cases [1595 cases on non-heat days, 17 cases on a heat day]

<sup>8</sup> While statistically significant, the estimate is based on a small number of cases [1113 cases on non-heat days, 16 cases on a heat day]

<sup>9</sup> While statistically significant, the estimate is based on a small number of cases [411 cases on non-heat days, 4 cases on a heat day]

<sup>10</sup> While statistically significant, the estimate is based on a small number of cases [417 cases on non-heat days, 5 cases on a heat day]

<sup>11</sup> While statistically significant, the estimate is based on a small number of cases [9 cases on non-heat days, 1 cases on a heat day]

Table 10.2: Time-series analysis results for ALS data. Percent changes in daily EMS calls presented for every 1 degree increase above 39.7 °C humidex (95% CIs). Data displayed by age category, medical issue, and level of transport.<sup>1</sup>

Medical Issue	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
All Causes	<b>3.8 (1.1, 6.5)</b>	4.2 (-11, 22)	2.1 (-17, 25)	1.9 (-3, 7)	<b>8 (3.5, 12)</b>	2.3 (-2.7, 7.5)	3.6 (-3.5, 11)
Trauma	-6.3 (-17, 5.3)	25 (-5.8, 65)	-4.7 (-45, 64)	-8.7 (-22, 6.7)	-8.5 (-28, 16)	-19 (-51, 34)	-2.1 (-45, 75)
Non-Trauma	<b>4.2 (1.3, 7.1)</b>	-7.1 (-26, 17)	-1.3 (-24, 28)	1.7 (-3.9, 7.6)	7.8 (3.5, 12)	2.2 (-2.9, 7.5)	4.2 (-2.9, 12)
Abdominal/Genito-Urinary	-2 (-12, 9.1)	69 (5.6, 169)	-42 (-95, 607)	11 (-9.4, 36)	-3.2 (-19, 16)	-9.5 (-28, 13)	-11 (-36, 23)
Alcohol/Drugs	-14 (-27, 2.5)	--	--	-18 (-35, 4.2)	-1.2 (-22, 25)	--	--
Anaphylaxis/Allergy	-15 (-37, 14)	-55 (-96, 473)	20 (-27, 97)	-79 (-99, 439)	2.8 (-27, 44)	--	--
Cardiovascular	-1.2 (-6.7, 4.5)	--	--	2.4 (-12, 19)	5.5 (-2.2, 13.7)	-8.3 (-17, 1.6)	-6.8 (-20, 8)
Metabolic/Endocrine	1.9 (-7.9, 13)	--	53 (-5, 148)	12 (-6.5, 33)	-12 (-29, 9.6)	5.7 (-10, 25)	-9.6 (-46, 51)
Diabetes	1.2 (-9.1, 13)	--	--	12 (-6.3, 34)	-9.8 (-28, 12)	6 (-10, 26)	-23 (-65, 66)
Neurological	5.4 (-1, 12.3)	-5.9 (-34, 35)	--	1.6 (-9.9, 1 5)	7.3 (-3.9, 20)	9.3 (-2.7, 23)	10.6 (-4.4, 28)
Suspected CVA	-2.6 (-21, 20)	-4.9 (-100, Inf)	--	--	-78 (-99, 560)	3.9 (-19, 33)	7.1 (-19, 42)
Suspected TIA	--	19 (-100, Inf)	20 (-100, Inf)	--	--	--	--
Seizure	-8.6 (-21, 6.2)	-34 (-75, 71)	--	-7.1 (-25, 16)	3.1 (-17, 29)	-12 (-50, 55)	--
Febrile Seizure	19 (-19, 74)	23 (-16, 79)	--	--	--	--	--
OBGYN	3.6 (-19, 32)	--	--	-2.8 (-26, 27)	<b>128 (36, 280)<sup>2</sup></b>	--	--
Other Medical	<b>18 (13, 24)</b>	1.2 (-36, 60)	28 (-18, 97)	<b>13 (0.6, 27)</b>	<b>21 (12, 30)</b>	<b>19 (9.3, 30)</b>	-9.6 (-46, 51)
Heat Illness & Dehydration	<b>49 (36, 63)</b>	-9.5 (-87, 512)	72 (1.3, 193)	<b>44 (17, 77)<sup>3</sup></b>	<b>50 (27, 77)<sup>4</sup></b>	<b>54 (32, 80)<sup>5</sup></b>	<b>41 (13, 77)<sup>6</sup></b>
Psychological	-4 (-17, 11)	--	--	-9.8 (-29, 14)	4.5 (-15, 28)	-7.5 (-43, 49)	-6.9 (-61, 121)
Respiratory	1.7 (-5.8, 9.9)	-16 (-53, 49)	-10 (-54, 74)	7.9 (-8.6, 27)	5.7 (-6.7, 20)	-5.5 (-19, 10)	4.3 (-13, 25)
Asthma	0.7 (-26, 37)	-33 (-92, 477)	--	17 (-18, 67)	-2.8 (-53, 102)	--	--
Emphysema/COPD	7.3 (-19, 41)	-7.4 (-100, Inf)	--	<b>100 (20, 235)<sup>7</sup></b>	16 (-22, 72)	-69 (-96, 142)	40.1 (-7, 111)

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ ); -- indicates too few cases available to calculate

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [17 cases on non-heat days, 1 cases on a heat day]

<sup>3</sup> While statistically significant, the estimate is based on a small number of cases [79 cases on non-heat days, 7 cases on a heat day]

<sup>4</sup> While statistically significant, the estimate is based on a small number of cases [129 cases on non-heat days, 11 cases on a heat day]

<sup>5</sup> While statistically significant, the estimate is based on a small number of cases [160 cases on non-heat days, 18 cases on a heat day]

<sup>6</sup> While statistically significant, the estimate is based on a small number of cases [88 cases on non-heat days, 6 cases on a heat day]

<sup>7</sup> While statistically significant, the estimate is based on a small number of cases [7 cases on non-heat days, 1 cases on a heat day]

Table 10.3: Time-series analysis results for BLS and ALS data. Percent changes in daily EMS calls presented for every 1 degree increase above 40.7 °C humidex (95 CIs) for BLS and above 39.7 °C humidex for ALS. Data displayed by age category and level of transport.<sup>1</sup>

Medical Issue	All Ages	Years					
		0-4	5-14	15-44	45-64	65-84	85+
<b>BLS Data</b>							
No Transportation	<b>10.9 (7.3, 14.6)</b>	<b>19.2 (5.6, 34.5)</b>	<b>18 (3.7, 34.3)</b>	<b>7.2 (1.8, 12.9)</b>	<b>16.0 (9.8, 22.6)</b>	<b>8.2 (0.7, 16.2)</b>	7.6 (-2.4, 18.7)
BLS Transport	<b>7.0 (4.5, 9.7)</b>	9.0 (-6.9, 27.6)	-1.7 (-17.1, 16.6)	<b>4.2 (0.1, 8.4)</b>	<b>8.0 (3.8, 12.4)</b>	<b>8.9 (4.1, 14)</b>	<b>9.7 (3.5, 16.3)</b>
ALS Transport	-1.1 (-6.7, 4.8)	-1.7 (-31.1, 40.3)	13.5 (-18.5, 58)	-4.2 (-14.5, 7.37)	3.2 (-5.4, 12.5)	-2.7 (-12.3, 8.1)	-6.4 (-21.1, 11.0)
Other Transport	3.8 (-3, 11.0)	-11.7 (-34.9, 19.9)	-22.5 (-46.9, 1)	8.2 (-1.6, 18.94)	-7.9 (-22.1, 8.9)	15.9 (0.5, 33.7)	20.2 (-3.7, 50)
<b>ALS Data</b>							
No Transportation	<b>10.02 (3.8, 16.6)</b>	15.7 (-15.3, 57.9)	10.9 (-22.1, 58.1)	<b>12.8 (3, 23.5)</b>	<b>12.8 (3, 23.5)</b>	3 (-10.6, 18.5)	-4.1 (-24.2, 21.2)
BLS Transport	<b>7.23 (3.39, 11.21)</b>	3.2 (-22.1, 36.6)	-15.8 (-51.7, 46.8)	-0.6 (-8.2, 7.6)	<b>11.9 (5.7, 18.4)</b>	<b>8.2 (0.9, 16.1)</b>	9.3 (-0.6, 20.0)
ALS Transport	-1.35 (-5.45, 2.93)	-0.3 (-23.2, 29.3)	7.9 (-17.0, 40.3)	-3 (-10.7, 5.4)	1.8 (-4.6, 8.6)	-3.8 (-11.1, 4.2)	-3.6 (-14.6, 8.8)
Other Transport	5.99 (-7.73, 21.75)	--	--	6 (-15.3, 32.6)	6.3 (-18.5, 38.6)	-2.1 (-33.3, 43.9)	<b>40.4 (5.4, 87.1)<sup>2</sup></b>

<sup>1</sup> Bolded relative risk values are significantly greater than 1 ( $p < 0.05$ ); -- indicates too few cases available to calculate

<sup>2</sup> While statistically significant, the estimate is based on a small number of cases [190 cases on non-heat days, 5 cases on a heat day]

## APPENDIX 11:

### RESULTS—COST ANALYSIS

On average, an ALS call cost approximately nine times a BLS call at \$963 and \$105 respectively [PHSKC 2012]. Since increases in costs were the result of both the average call costs and average daily call counts, ALS calls had the greatest increases in cost for all causes, trauma, and non-trauma. For all causes and non-trauma, BLS calls using the 95<sup>th</sup> percentile threshold had the lowest increases in costs (\$3,142 and \$1,676 respectively) while BLS calls using the 99<sup>th</sup> percentile had the lowest increase in cost for trauma (\$587). Please see table 11.1 and Figure 11.1.

		All Causes	Trauma	Non-Trauma
Table 11.1: Analysis of average costs of EMS calls on non heat days compared to 95th (29.7 °C) or 99th (36.7 °C) percentile heat days for BLS and ALS EMS calls. Table includes average daily number of calls on non heat days and heat days, the average total cost of those calls, and the difference in costs as heat day costs minus non heat day costs. Average daily counts of EMS calls are sourced from the relative risk analysis while average costs are sourced from the 2012 King County Annual Report. Average cost per call as calculated from this report is 104.7 for BLS and 962.8 for ALS.				
BLS 95th %ile All Ages	Non heat day average call count	390.0	50.5	257.0
	Non heat day average cost	40,842.6	5,288.6	26,914.2
	Heat day average call count	420.0	56.7	273.0
	Heat day average cost	43,984.3	5,937.9	28,589.8
	<b>Difference in costs</b>	<b>3,141.7</b>	<b>649.3</b>	<b>1,675.6</b>
BLS 99th %ile All Ages	Non heat day average call count	392.0	51.1	258.0
	Non heat day average cost	41,052.0	5,351.4	27,018.9
	Heat day average call count	455.0	56.7	300.0
	Heat day average cost	47,649.7	5,937.9	31,417.4
	<b>Difference in costs</b>	<b>6,597.6</b>	<b>586.5</b>	<b>4,398.4</b>
ALS 99th %ile All Ages	Non heat day average call count	103.0	6.7	89.3
	Non heat day average cost	99,165.0	6,402.4	85,975.1
	Heat day average call count	117.0	7.5	100.0
	Heat day average cost	112,643.7	7,220.8	96,276.7
	<b>Difference in costs</b>	<b>13,478.7</b>	<b>818.4</b>	<b>10,301.6</b>

**Figure 11.1: Difference in Average Daily Costs on a Heat Day Compared to a Non-Heat Day**

