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Estimating associations between high temperature and emergency department visits in six US  
cities with the use of 1-kilometer temperature products

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Bachelor of Engineering

Vanderbilt University

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Thesis Advisor: Howard H. Chang, PhD.

An abstract of

A thesis submitted to the Faculty of the

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2020

## Abstract

Estimating associations between high temperature and emergency department visits in six US cities with the use of 1-kilometer temperature products

By Nikita Thomas

**Background:** High temperatures have significant impacts on society – an effect that is increasing due to climate change and increasingly frequent heat wave events. Exposure to high temperatures has been shown to result in higher rates of emergency department visits. Previous studies typically utilize temperature data collected at airports to define exposures. However, this may not be representative of the true temperature felt by the population, due to the location of airports being situated far from urban areas.

**Methods:** We use the gridded climate dataset, Daymet, to create three temperature metrics, including two that account for county and ZIP code level populations, for both minimum and maximum temperatures during the warm season (May-September) in six US cities. We use a Poisson log-linear model to estimate the association of temperatures and emergency department visits during the warm season for six health outcomes. We then plot to compare estimated relative risk as determined by the Daymet metrics and the airport monitor metric.

**Results:** We observed that the Daymet metrics were highly correlated ( $\geq 0.90$ ) with the airport monitor metrics for all cities except San Francisco and Los Angeles. We also observed that acute renal failure, fluid and electrolyte imbalance, and heat related illnesses most consistently had higher relative risk predictions associated with the finer scale temperature metrics.

**Conclusions:** We found evidence that using finer scale temperature metrics is useful in estimating relative risks of various health outcomes, particularly for cities that have high exposure variability.

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## Table of Contents

- I.** Introduction
- II.** Methods
  - a.** Data Sources and Processing
  - b.** Statistical Analysis
- III.** Results
- IV.** Discussion
- V.** Tables and Figures
  - a.** Table 1. Descriptive statistics for emergency department (ED) visits from May to September in each city.
  - b.** Table 2. Descriptive statistics for four temperature metrics during May to September in each city
  - c.** Figure 1. Relative risk of selected health outcomes vs maximum temperature during May to September in Atlanta, 1993-2012.
  - d.** Figure 2. Relative risk of selected health outcomes vs minimum temperature during May to September in Atlanta, 1993-2012.
  - e.** Figure 3. Relative risk of selected health outcomes vs maximum temperatures during May to September in San Francisco, 2005-2016
  - f.** Figure 4. Relative risk of selected health outcomes vs minimum temperatures during May to September in San Francisco, 2005-2016
  - g.** Figure 5. Relative risk of selected health outcomes vs maximum temperature during May to September in Los Angeles, 2005-2016

- h.** Figure 6. Relative risk of selected health outcomes vs minimum temperature during May to September in Los Angeles, 2005-2016
- i.** Figure 7. Relative risk of selected health outcomes vs maximum temperature during May to September in Salt Lake City, 2005-2016
- j.** Figure 8. Relative risk of selected health outcomes vs minimum temperature during May to September in Salt Lake City, 2005-2016
- k.** Figure 9. Relative risk of selected health outcomes vs maximum temperature during May to September in Newark, 2005-2016
- l.** Figure 10. Relative risk of selected health outcomes vs minimum temperature during May to September in Newark, 2005-2016
- m.** Figure 11. Relative risk of selected health outcomes vs maximum temperature during May to September in Phoenix, 2008-2016
- n.** Figure 12. Relative risk of selected health outcomes vs minimum temperature during May to September in Phoenix, 2008-2016

## **VI.** References

## I. Introduction

High temperatures are known to have significant impacts on several societal factors, including the economy and public health.<sup>1</sup> Exposure to high temperature is increasing due to climate change.<sup>2</sup> Extreme temperature events (i.e., heat waves) are also increasing in frequency, duration, and magnitude and future events are projected to be more intense and longer lasting.<sup>2,3</sup> There is evidence in the literature indicating that exposures to high temperature are associated with an increase in mortality<sup>4,5</sup> and morbidity. Large urban areas are expected to be most significantly impacted by future warming events due to the urban heat island effect.<sup>6</sup>

Previous epidemiologic studies have established the impact of high temperature on mortality.<sup>7,8</sup> A study of the effects of heat waves in 43 US communities indicated higher mortality risks from heat waves of higher intensity or duration.<sup>5</sup> Extreme temperature events specifically have been found to exacerbate respiratory, cardiovascular, renal diseases, and diabetes mellitus.<sup>2,7-9</sup> Specific populations have been found to be more susceptible to health effects associated with high temperature, including elderly, infants and children, pregnant women, outdoor workers, populations of low socioeconomic status, populations with existing adverse health conditions and disability, and populations without access to air conditioning.<sup>2,6-10</sup>

There have been a large number of studies examining the relationship between exposure to high temperature and mortality and fewer studies on heat wave impact on population morbidity through emergency department (ED) visits.<sup>5,7,8,10-12</sup> Previous studies examining warm season associations between temperature and daily ED visits in Atlanta have used daily temperature data collected at the Hartsfield-Jackson airport.<sup>10-12</sup> The use of airport weather station data is a common practice because of its long historical monitoring period with complete daily measurements. However, temperature data collected at airports may not be necessarily an



accurate representation of the true temperature experienced by populations in large urban areas due to the nature of airports generally being located in areas away from large populations.

Several meteorological data products have been developed recently by combining monitoring measurements, elevation, numerical model simulations and satellite-derived parameters. PRISM<sup>13</sup> and DayMet<sup>14</sup> are two products with data available starting in 1980 at 4km and 1km resolution, respectively. PRISM and Daymet have been found to accurately estimate ambient temperature and mean heat index at weather stations.<sup>15</sup> Because gridded products have complete spatial coverage, they offer potential in reducing exposure measurement error compared to use of airport-based weather stations for estimating population exposures to meteorological variables.<sup>15</sup> To more accurately assess exposure of extreme temperature on populations in urban areas, one approach is to account for population distribution. Specifically, spatially-resolved (i.e., gridded) temperature estimates can be weighted by the county and ZIP code-level population counts.

Few studies have considered using gridded data products for conducting epidemiological analyses of health effects due to high temperature. In particular, the use of gridded temperature products in epidemiologic studies for assessing exposure of urban populations has not yet been compared to the use of temperature data collected at airport monitors. In this paper, we examine associations between daily emergency department visits in six US cities and exposure to daily maximum and minimum temperature derived using the 1-km Daymet data product in six US cities.

## **II. Methods**

### *Data Sources and Processing*

Daymet surface weather data were simulated throughout the North American continent, providing gridded estimates with 1km x 1 km spatial resolution.<sup>16</sup> Data were accessed from the Oak Ridge National Laboratory website and include daily maximum and minimum temperatures for each of the 1 km grid points in six cities of interest (Atlanta, San Francisco, Los Angeles, Salt Lake City, Phoenix, and Newark).<sup>14</sup>

Airport monitor meteorological data were collected from the National Oceanic and Atmospheric Administration<sup>17</sup> for each of the six metropolitan areas. For this analysis, daily maximum, daily minimum temperatures, and dewpoint temperature were utilized.

We considered different ways to utilize the 1 km gridded surface weather data to compare with daily measurements at the airport monitor. Daymet temperature data were used to develop three different exposure temperature metrics: a simple daily average of all 1km grid cells over each metropolitan area, a daily weighted average based on county population, and a daily weighted average based on ZIP code population. The exposure metrics were created for daily maximum and minimum temperatures, ultimately creating four different metrics for maximum and minimum temperatures. The population weighted averages were calculated using the equation:

$$Temp_{t,weighted} = \frac{\sum Pop_i * Temp_{it}}{\sum Pop_i}$$

where  $Temp_{it}$  is the maximum or daily temperature on day  $t$  in county/ZIP code  $i$ . Calculating exposures that incorporate spatial distributions of the at-risk population may provide a more accurate measure of the temperature experienced by the populations of each of the cities.

Data on population size were collected using publicly available census data. Data were collected at the county level from the 1990, 2000, and 2010 censuses and at the ZIP code level from the 2000 and 2010 censuses. County and ZIP code shapefiles were downloaded as TIGER

files from the US Census for each of the five states.<sup>18</sup> County- and ZIP code-level population data were interpolated linearly between Census time points in order to estimate population numbers during non-census years.

The R packages, `rgdal`, `rgeos`, `raster`, `maptools`, and `spdep` were used to align the 1 km x 1 km Daymet data to each county and ZIP code. Nearest neighbor methods were utilized to determine which grid points were associated with each county and ZIP code. To account for variability in ZIP code boundaries between census time points, ZIP code boundaries for 2000 were used for data from 1993-2005, and boundaries for 2010 were used for data from 2006-2016. Any ZIP codes that did not appear in both 2000 and 2010 censuses were excluded from the analysis to allow for continuity in the data set.

Each metropolitan area was defined at the county-level by using the metropolitan statistical area (MSA) definition and at the ZIP code-level by determining which ZIP code tabulation areas (ZCTA) overlapped with the MSA definition. In each of the metropolitan areas, patient-level emergency department visit records were collected from individual hospitals, state departments of public health, or hospital associations. Daily ED visits were selected where patient residential ZIP codes and hospital locations were in the MSA. We used the primary and secondary diagnosis codes (ICD-9 and ICD-10) to identify ED visits for specific health outcomes. The health outcomes of interest for this study were circulatory disease (ICD-9: 390-459, ICD-10: I00-I99), acute renal failure (ICD-9: 584, ICD-10: N17), fluid and electrolyte imbalance (ICD-9: 276, ICD-10: E86-E87), gastrointestinal infections (ICD-9: 001-009, ICD-10: A00-A09), heat-related illnesses (ICD-9: 992, ICD-10: T67), and respiratory disease (ICD-9: 460-519, ICD-10: J00-J99). For each of these outcomes, ED visits were aggregated over the city based on admission date.

All analysis was conducted in R, version 3.6.1 in RStudio. Other packages used included the R package, splines, in order to model the exposure and outcome relationships.

### *Statistical Analysis*

To assess the difference between temperature metrics derived from Daymet and the airport monitor, we calculated the means and standard deviations of each metric during the warm season (May to September) in each city, as well as the Pearson correlations between the daily values from each Daymet metric and the airport monitor.

To estimate the association of temperature and emergency department visits during warm seasons in each city, we used a Poisson log-linear model. The counts of each of the six health outcomes were modeled using a modified version of a previously developed model<sup>11</sup> and is specified as:

$$\log(\mu_t^a) = \beta_0 + ns(Tem_t) + ns(DPT_t) + \sum_{k=1}^{k=6} \gamma_k DOW_{tk} + \sum_{k=1}^{k=2} \delta_k HOLIDAY_{tk} + \sum_{k=1}^{k=42} \xi_k HOSPITAL_{tk} + ns(DATE_t)$$

where  $\mu_t^a$  is the expected number of ED visits for health outcome  $a$  on day  $t$ ;  $Tem_t$  is the temperature (in Celsius) on day  $t$ , modeled as a smooth function using natural cubic splines with 4 degrees of freedom to account for potential non-linear relationships with ED visits;  $DPT_t$  is the maximum dewpoint temperature (in Celsius) on day  $t$  to capture the strongest level of human discomfort during the day, also modeled as a smooth function using natural cubic splines with 4 degrees of freedom;  $DOW_{tk}$  is defined as the categorical variable for day  $k$  of the week on day  $t$ ;  $HOLIDAY_{tk}$  includes binary variables that indicate days on which federal holidays are observed;  $HOSPITAL_{tk}$  denotes hospital indicators to account for hospitals' contributions to the total ED visits in the city of interest, coded 1 when hospital  $k$  contributes ED visits on day  $t$ ; and  $DATE_t$

includes a smooth function of day of the warm season with monthly knots across years and a year-specific linear function for day of the warm season to capture differences between the years<sup>12</sup>.

The model was run for each city, health outcome, and eight temperature metrics (four for maximum and four for minimum, represented as the *Tem* term in the model). The model coefficients of the temperature spline terms were used to calculate the non-linear relative risk of cause-specific ED visits associated with a degree Celsius increase in temperature. The exposure-response functions were then plotted across the observed temperature values for each of the four temperature metrics in each city. Relative risks were centered so that a relative risk of 1 was associated with the 25<sup>th</sup> percentile of the maximum/minimum airport temperatures. We set the 25<sup>th</sup> percentile as a reference temperature to better visualize the risks associated with higher temperature.

### **III. Results**

The total and mean daily ED visits for each of the six health outcomes of interest in each of the six US cities are shown in Table 1. In Table 2, the means and correlations of the four temperature metrics for each city are shown. The three Daymet metrics were highly correlated ( $\geq 0.90$ ) with the airport metric for all cities except Los Angeles and San Francisco. There was variation between each of the cities regarding their temperatures. San Francisco and Los Angeles had lower temperatures across the four metrics, but the airport monitor temperatures for these two cities was also considerably lower than the other three metrics for maximum temperature while it was consistent for minimum temperature. Phoenix tended to have much higher temperatures across all four metrics than any of the other cities – this is attributable to its geographic location in the southwestern United States.

Figures 1 and 2 show relative risks of daily ED visits associated with maximum/minimum temperature in Atlanta. Overall, we found positive associations between temperature and ED visits for all outcomes. For acute renal failure, fluid/electrolyte imbalance, heat related illnesses, and gastrointestinal infections, use of finer scale maximum temperature metrics resulted in stronger associations than use of airport temperature data alone (Figure 1). For minimum temperature (Figure 2), similar observations can be made for respiratory illnesses, heat related illnesses, and acute renal failure. We note that for Atlanta, we found that the range of minimum temperature from Daymet was considerably different from that observed at airport monitor, an observation that is also evident in Table 2.

Figures 3 and 4 show relative risks of daily ED visits associated with maximum/minimum temperature in San Francisco during the warm season from 2005 to 2016. In Figure 3, it can be observed that for heat related illnesses, acute renal failure, circulatory diseases, and fluid and electrolyte balance, positive associations with maximum temperature were observed for each temperature metric. It should be noted strong associations were seen with the use of finer spatial population weighting, i.e., the ZIP code population weighted model for acute renal failure. In Figure 4 for minimum temperature, the Daymet metrics again gave higher relative risks for all outcomes with the ZIP code population metric having the strongest association.

Relative risks for daily maximum and minimum temperatures in Los Angeles are depicted in Figures 5 and 6. In Figure 5, heat related illness and gastrointestinal infections are seen to have a higher relative risk associated with all the finer scale temperature metrics. However, the confidence intervals are wide for all of the outcomes, indicating significant

variability in the relative risk estimates. In Figure 6 for minimum temperature, none of the Daymet metrics gave higher relative risks compared to the airport temperature.

Figures 7-12 depict the relative risk vs temperature plots for Salt Lake City, Newark, and Phoenix, with similar observations.

#### **IV. Discussion**

In this study, we used the fine scale temperature dataset, Daymet, to develop three different temperature metrics for each city: an unweighted daily average, a county population weighted daily average, and a ZIP code population weighted daily average. Along with the airport temperature metric, each of these metrics was used in our Poisson log-linear model to determine the association between the temperature metrics and emergency department visits for six health outcomes, for both maximum and minimum temperatures. We found that there was variation among the all of the cities between the Daymet metrics and the airport monitor metrics. Among all cities, we found that heat related illnesses, acute renal failure, and fluid and electrolyte balance consistently had positive associations for maximum temperatures across all four metrics. For minimum temperatures, circulatory and respiratory diseases had positive associations in Atlanta, San Francisco, Newark, and Phoenix.

From the results, we demonstrate the advantage of using finer scale temperature products to estimate exposures. This potentially reduces exposure measurement error and results in more accurate representation of the relative risk of ED visits associated with high temperatures. This observation is apparent for some cities more so than others. Analysis for San Francisco, Salt Lake City, Phoenix, and Los Angeles would benefit from using a temperature metric that is weighted at the ZIP code level rather than any of the other metrics. For Atlanta and Newark, the three weighting schemes of Daymet data gave similar results, but all estimated higher relative

risks when compared to the airport temperature metric. This may be explained by the greater variation in the terrains of the cities in the western half of the United States while Atlanta and Newark do not have as much geographic variability.

It is also clear that using a finer temperature metric is more essential for heat sensitive diseases. Acute renal failure, fluid and electrolyte imbalance, and heat related illnesses consistently had higher relative risk predictions associated with the finer scale temperature metrics, while circulatory, respiratory, and gastrointestinal illnesses varied depending on the city and the specific daily temperature type (maximum or minimum). This may be due to the former three illnesses acutely presenting within a short amount of time after high temperature exposure while the latter three illnesses may only present themselves after longer term exposure.

While analyzing maximum temperature is important when determining the association between high temperatures and emergency department visits, analysis of minimum temperature provides insight into the health relevance of temperatures that individuals are exposed to overnight. The ZIP code population weighted metric consistently gave the strongest relative risks associated with the minimum daily temperature. For Atlanta, San Francisco, Newark, and Phoenix, using the Daymet-derived minimum temperature in the analysis yielded stronger associations for circulatory and/or respiratory diseases, while for maximum temperature analysis we did not observe differences in estimated relative risk across different temperature metrics. The ZIP code metric may have provided the strongest relative risks associated with minimum daily temperature since this reflects the temperature that individuals are exposed to when they are at home, often asleep. This metric most accurately suggests the temperatures the population is exposed to that may lead to the development of a specific disease.



We have shown that using finer scale temperature metric results in strong estimates of relative risks for five disease outcomes in the context of emergency department visits. In future analyses, it would be worthwhile to consider other disease outcomes as well as stratified analysis by specific demographics, particularly age and race groups. The availability of ZIP code-level temperature metrics would also provide the opportunity to conduct analyses into which ZIP code populations may be at higher risk for heat-related adverse health outcomes during the warm season.

## Tables and Figures

Table 1. Descriptive statistics for emergency department (ED) visits from May to September in each city.

<b>Metric</b>	<b>Total ED Visits</b>	<b>Mean Daily ED Visits</b>
<b>Atlanta, 1993-2012</b>		
Fluid and Electrolyte Imbalance	66369	22
Acute Renal Failure	109106	36
Circulatory Diseases	1905253	622
Respiratory Diseases	900570	294
Gastrointestinal Infections	30610	10
Heat Related Illnesses	12133	4
<b>San Francisco, 2005-2016</b>		
Fluid and Electrolyte Imbalance	459468	251
Acute Renal Failure	115851	63
Circulatory Diseases	1518306	827
Respiratory Diseases	898662	490
Gastrointestinal Infections	31561	18
Heat Related Illnesses	2923	2
<b>Los Angeles, 2005-2016</b>		
Fluid and Electrolyte Imbalance	1206667	658
Acute Renal Failure	325517	178
Circulatory Diseases	3689636	2010
Respiratory Diseases	2115910	1153
Gastrointestinal Infections	78230	43
Heat Related Illnesses	8860	5
<b>Salt Lake City, 2005-2016</b>		
Fluid and Electrolyte Imbalance	90930	50
Acute Renal Failure	14127	8
Circulatory Diseases	176262	96
Respiratory Diseases	124580	67
Gastrointestinal Infections	7032	4
Heat Related Illnesses	176262	1
<b>Newark, 2005-2016</b>		
Fluid and Electrolyte Imbalance	26979	15
Acute Renal Failure	757	1
Circulatory Diseases	275057	150
Respiratory Diseases	267431	146
Gastrointestinal Infections	3069	2
Heat Related Illnesses	1010	1
<b>Phoenix, 2008-2016</b>		
Fluid and Electrolyte Imbalance	269571	196
Acute Renal Failure	58531	43
Circulatory Diseases	689086	500
Respiratory Diseases	491364	357
Gastrointestinal Infections	14256	11
Heat Related Illnesses	5887	4

Table 2. Descriptive statistics for four temperature metrics during May to September in each city

Temperature Metric	Airport	Daymet Average	County Population Weighted Average	ZIP Population Weighted Average
<b>Atlanta, 1993-2012</b>				
Daily Max Temperature °C [Mean (SD)]	29.4 (3.7)	29.7 (3.4)	29.8 (3.4)	29.8 (3.4)
Daily Min Temperature °C [Mean (SD)]	19.9 (3.4)	17.8 (3.6)	17.9 (3.6)	17.9 (3.6)
Airport TMX Correlation	-	0.91	0.92	0.92
Airport TMN Correlation	-	0.93	0.93	0.93
<b>San Francisco, 2005-2016</b>				
Daily Max Temperature °C [Mean (SD)]	21.6 (3.7)	24.2 (3.9)	24.9 (4.0)	23.6 (3.7)
Daily Min Temperature °C [Mean (SD)]	12.8 (1.8)	12.2 (2.1)	12.7 (2.2)	12.4 (1.9)
Airport TMX Correlation	-	0.82	0.80	0.86
Airport TMN Correlation	-	0.79	0.73	0.83
<b>Los Angeles, 2005-2016</b>				
Daily Max Temperature °C [Mean (SD)]	23.0 (3.1)	28.4 (4.1)	29.0 (4.3)	27.8 (3.9)
Daily Min Temperature °C [Mean (SD)]	16.8 (2.2)	15.9 (3.0)	15.6 (3.2)	16.3 (2.6)
Airport TMX Correlation	-	0.75	0.70	0.84
Airport TMN Correlation	-	0.87	0.84	0.93
<b>Salt Lake City, 2005-2016</b>				
Daily Max Temperature °C [Mean (SD)]	29.2 (6.5)	24.7 (5.7)	25.8 (5.8)	27.2 (5.9)
Daily Min Temperature °C [Mean (SD)]	15.0 (5.5)	9.8 (4.6)	12.1 (4.9)	13.2 (5.0)
Airport TMX Correlation	-	0.98	0.98	0.98
Airport TMN Correlation	-	0.97	0.97	0.97
<b>Newark, 2005-2016</b>				
Daily Max Temperature °C [Mean (SD)]	27.5 (5.1)	26.6 (4.4)	26.8 (4.5)	26.9 (4.5)
Daily Min Temperature °C [Mean (SD)]	17.7 (4.5)	15.2 (4.4)	15.5 (4.4)	15.7 (4.4)
Airport TMX Correlation	-	0.90	0.91	0.92
Airport TMN Correlation	-	0.96	0.97	0.97
<b>Phoenix, 2008-2016</b>				
Daily Max Temperature °C [Mean (SD)]	39.1 (4.2)	37.1 (3.8)	37.6 (4.0)	38.4 (4.0)
Daily Min Temperature °C [Mean (SD)]	26.2 (4.3)	21.5 (4.2)	22.2 (4.3)	23.3 (4.3)
Airport TMX Correlation	-	0.96	0.97	0.98
Airport TMN Correlation	-	0.95	0.95	0.96

### Figure Legend

Vertical axes are drawn at 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup>, 95<sup>th</sup>, and 99<sup>th</sup> percentiles of the airport temperature measurements. Models for the four temperature metrics, airport temperature (TMX/TMN), Daymet average (DaymetAvg), county population weighted Daymet average (CountyWAvg), and ZIP code population weighted Daymet average (ZipWAvg) are indicated by different colors, with dashed lines showing 95% confidence bounds.

Figure 1. Relative risk of selected health outcomes vs maximum temperature during May and September in Atlanta, 1993-2012.

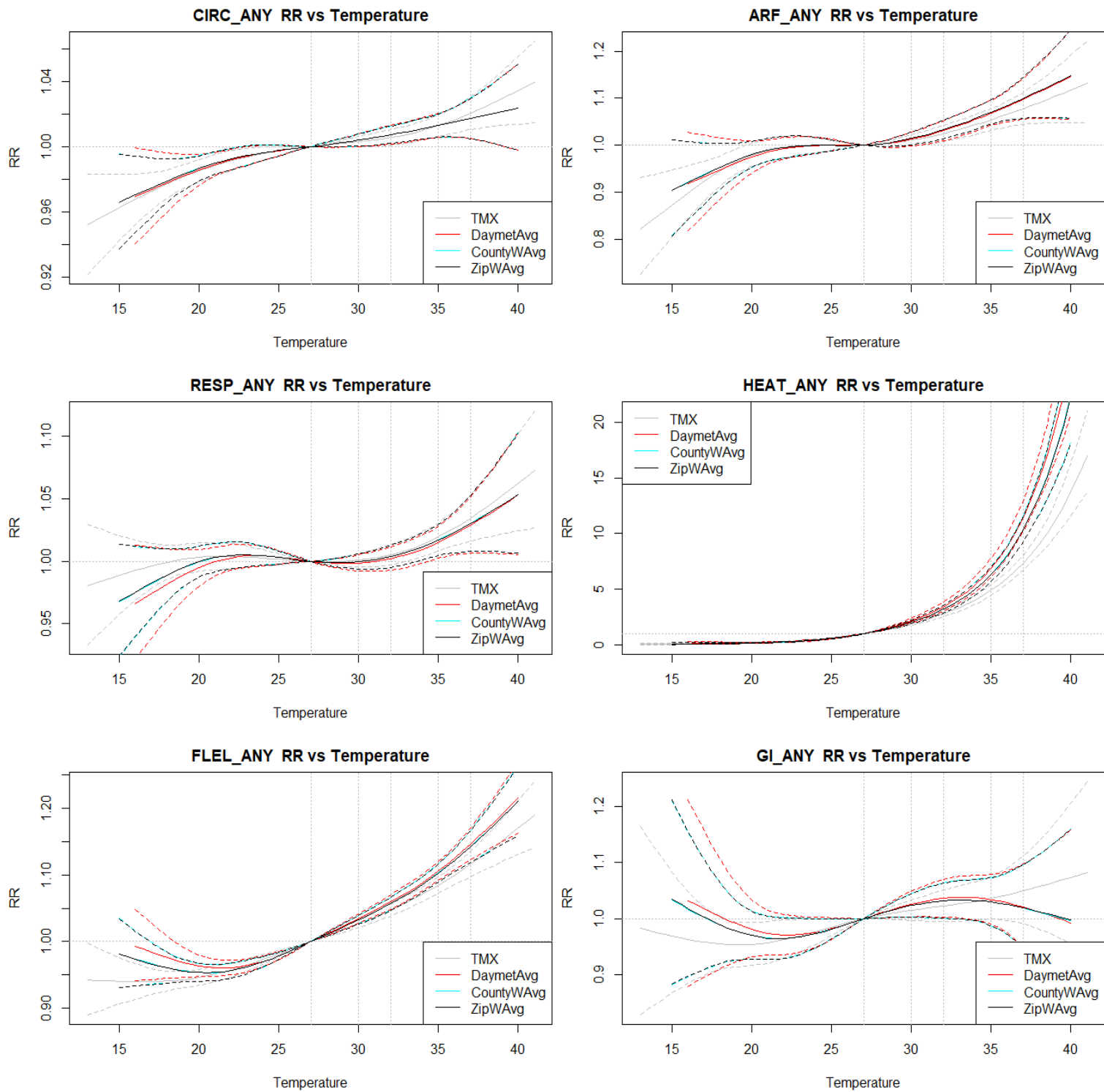
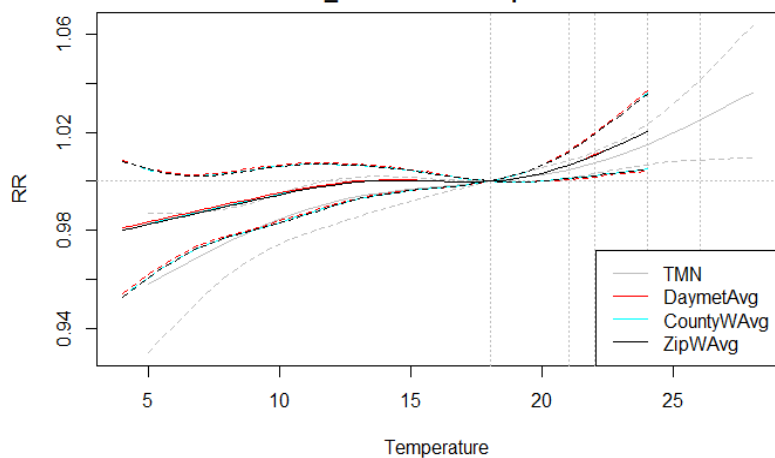
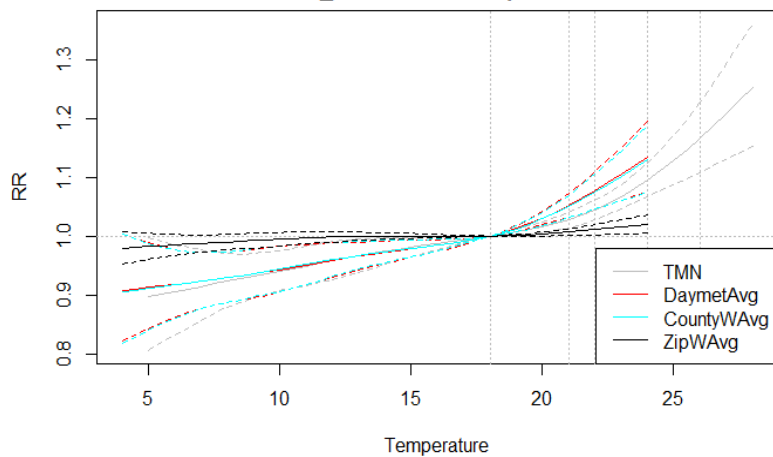


Figure 2. Relative risk of selected health outcomes vs minimum temperature during May to September in Atlanta, 1993-2012

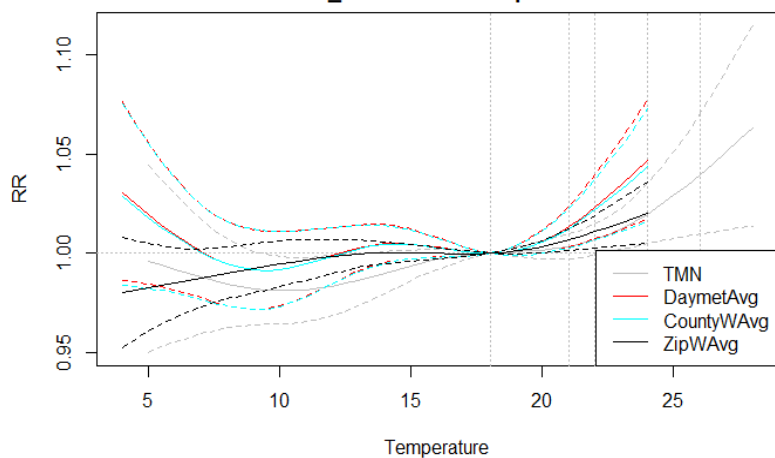
**CIRC\_ANY RR vs Temperature**



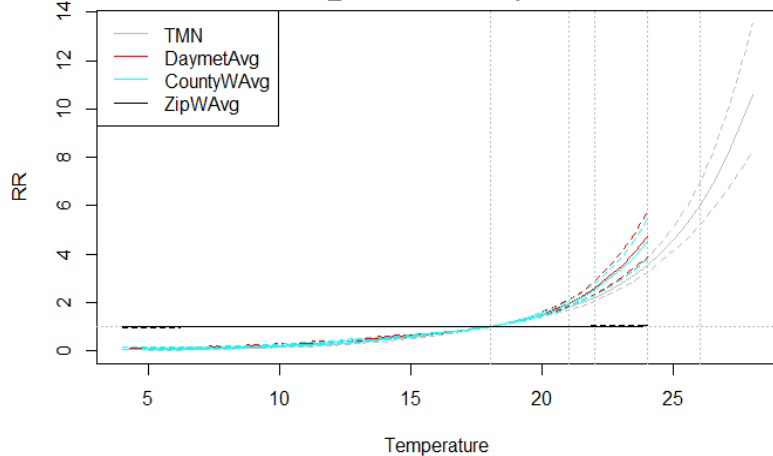
**ARF\_ANY RR vs Temperature**



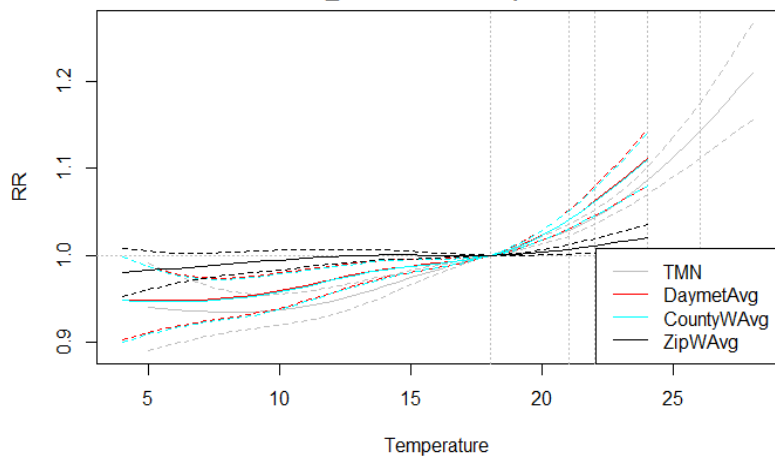
**RESP\_ANY RR vs Temperature**



**HEAT\_ANY RR vs Temperature**



**FLEL\_ANY RR vs Temperature**



**GI\_ANY RR vs Temperature**

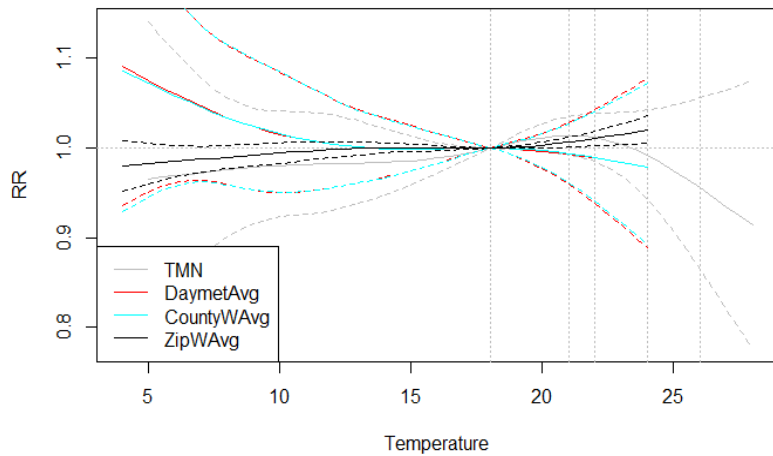


Figure 3. Relative risk of selected health outcomes vs maximum temperatures during May to September in San Francisco, 2005-2016

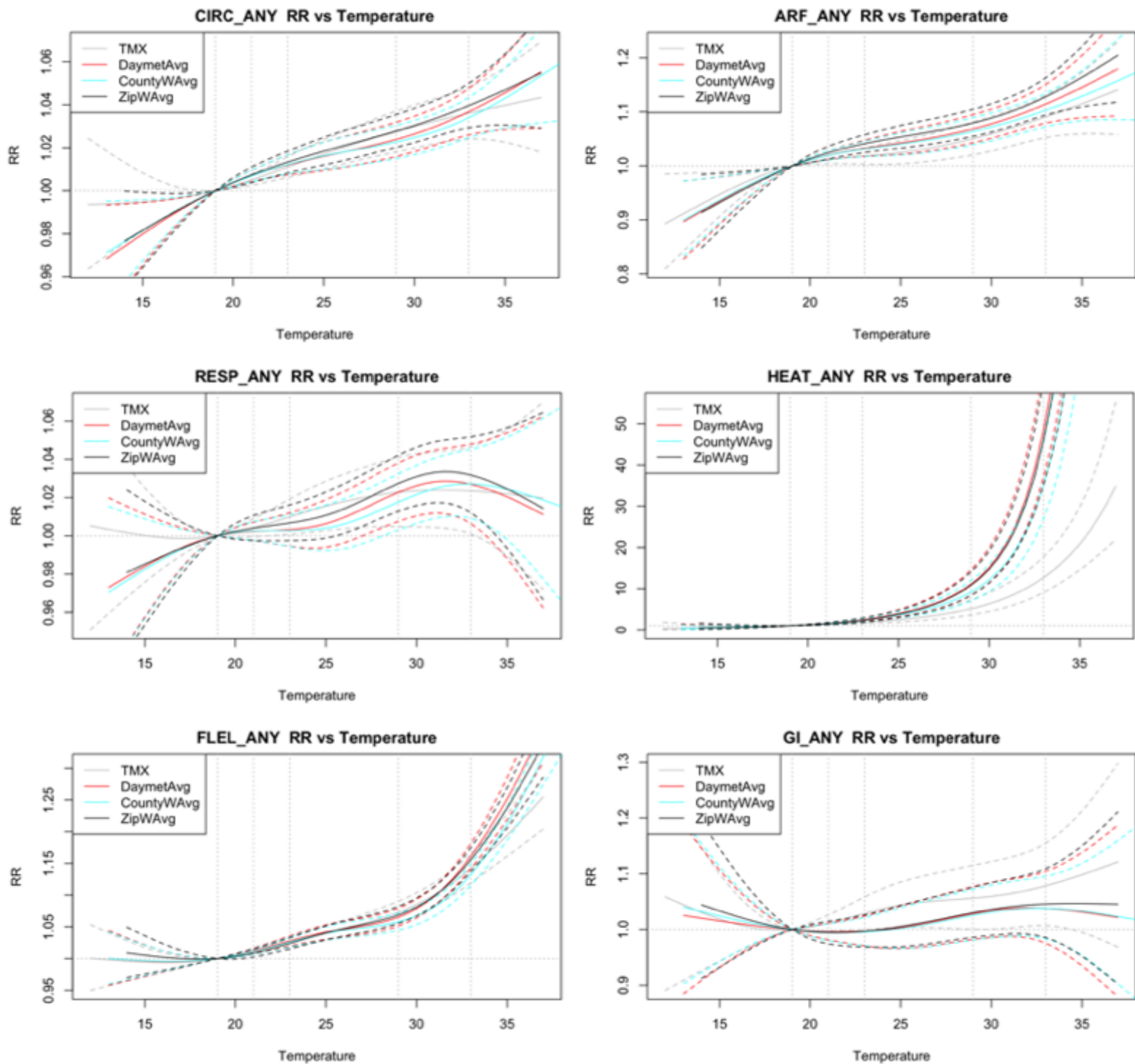


Figure 4. Relative risk of selected health outcomes vs minimum temperature during May to September in San Francisco, 2005-2016

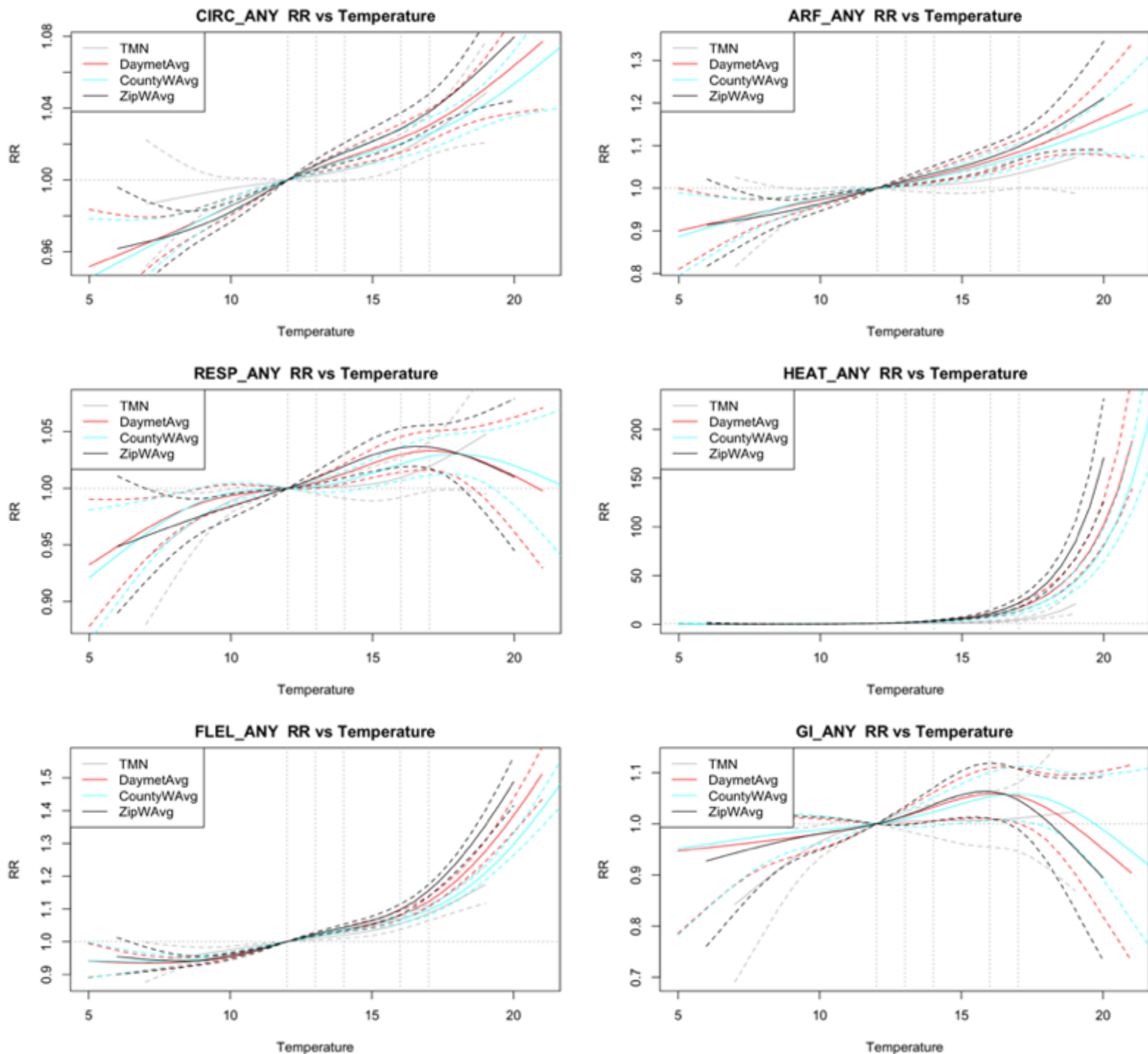




Figure 5. Relative risk of selected health outcomes vs maximum temperature during May to September in Los Angeles, 2005-2016

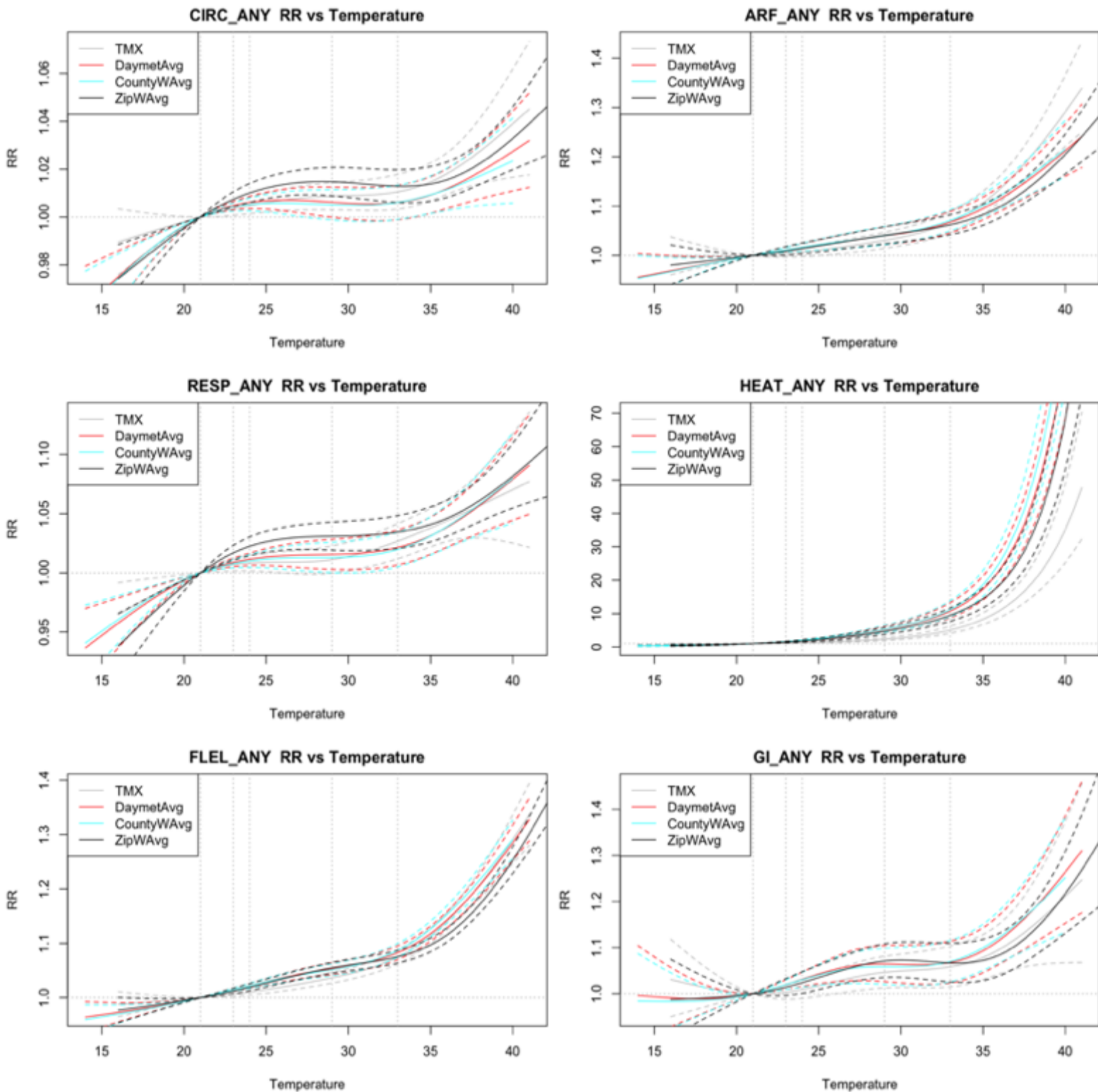


Figure 6. Relative risk of selected health outcomes vs minimum temperature during May to September in Los Angeles, 2005-2016

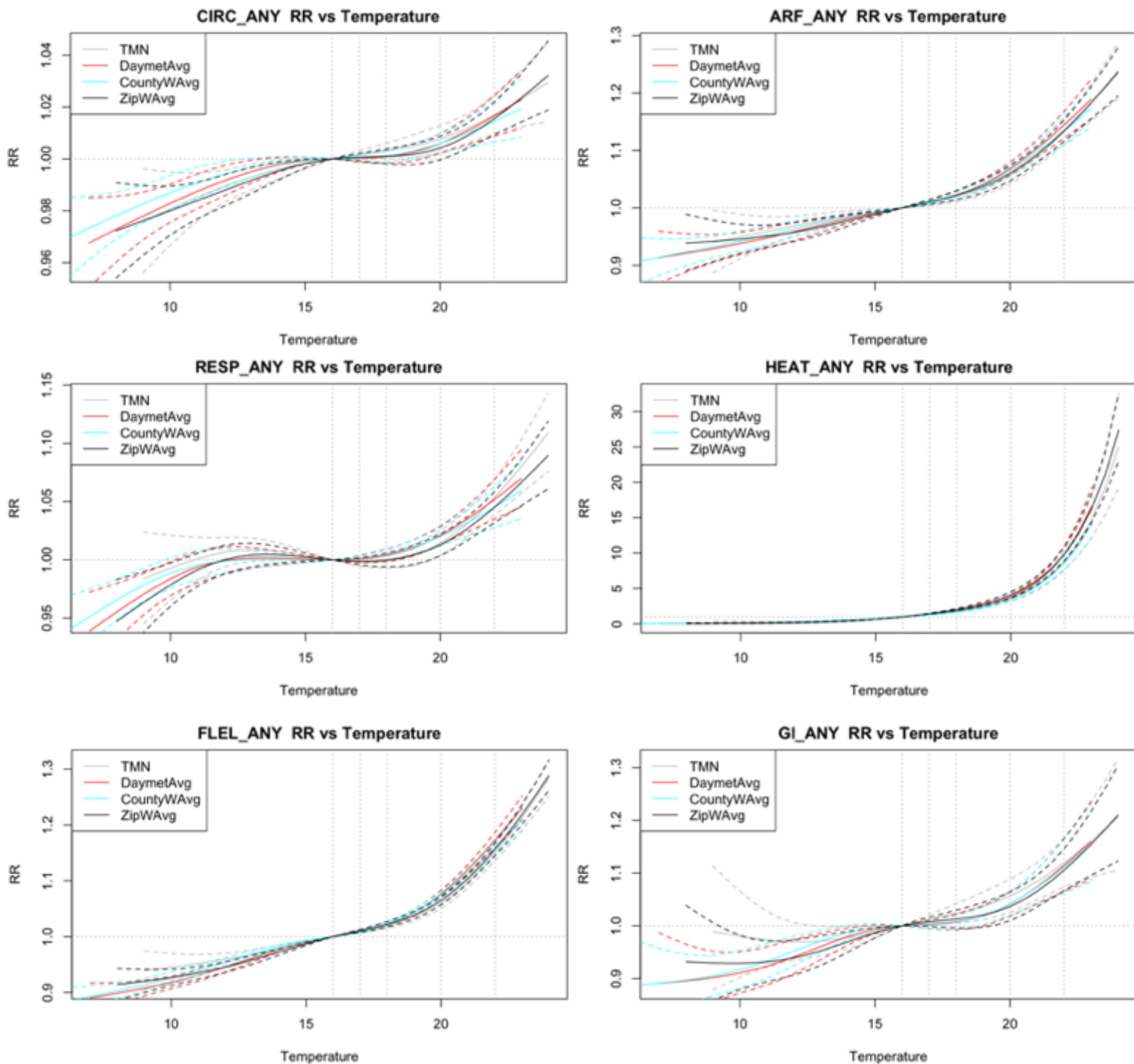


Figure 7. Relative risk of selected health outcomes vs maximum temperature during May to September in Salt Lake City, 2005-2016

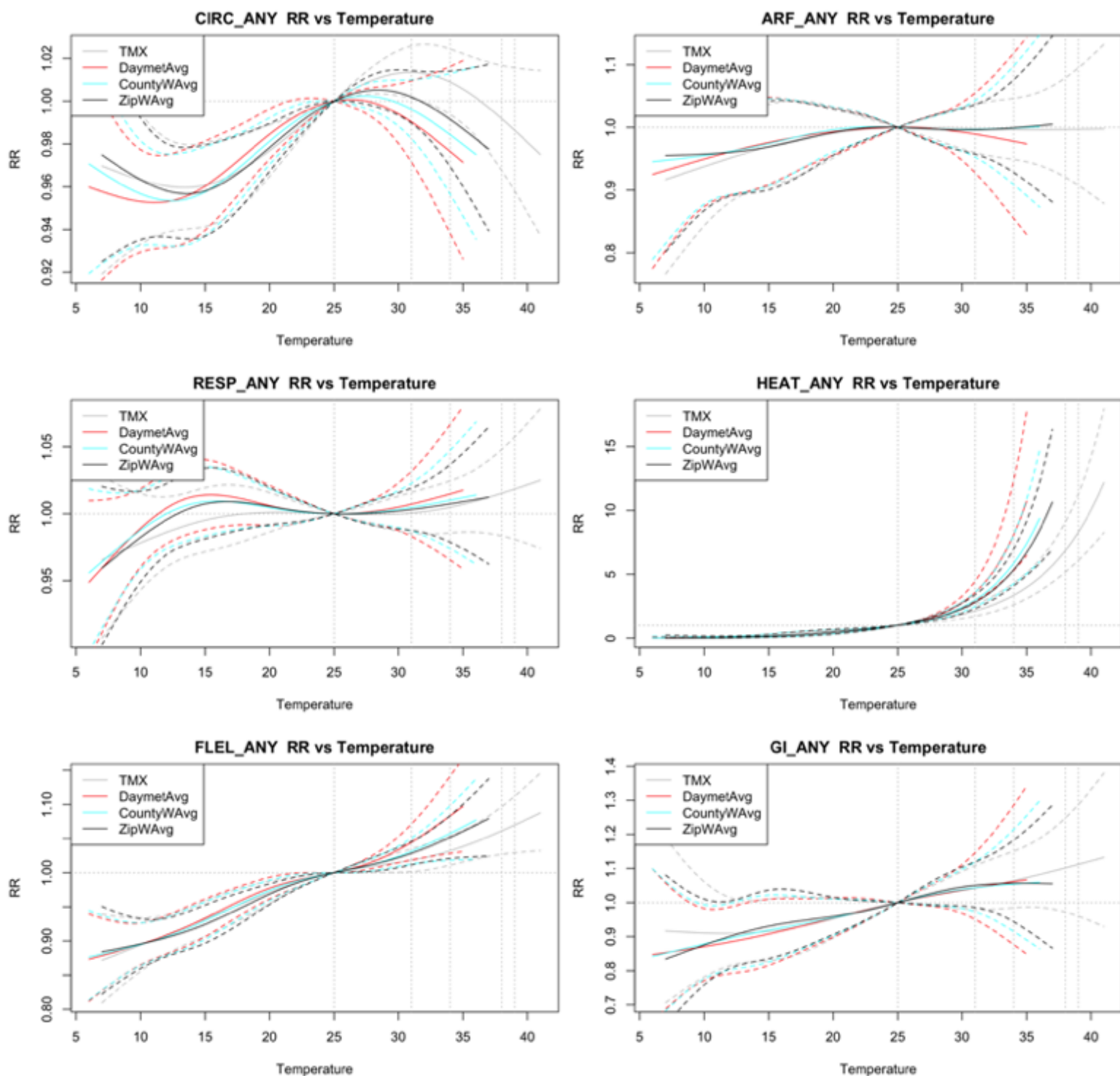


Figure 8. Relative risk of selected health outcomes vs minimum temperature during May to September in Salt Lake City, 2005-2016

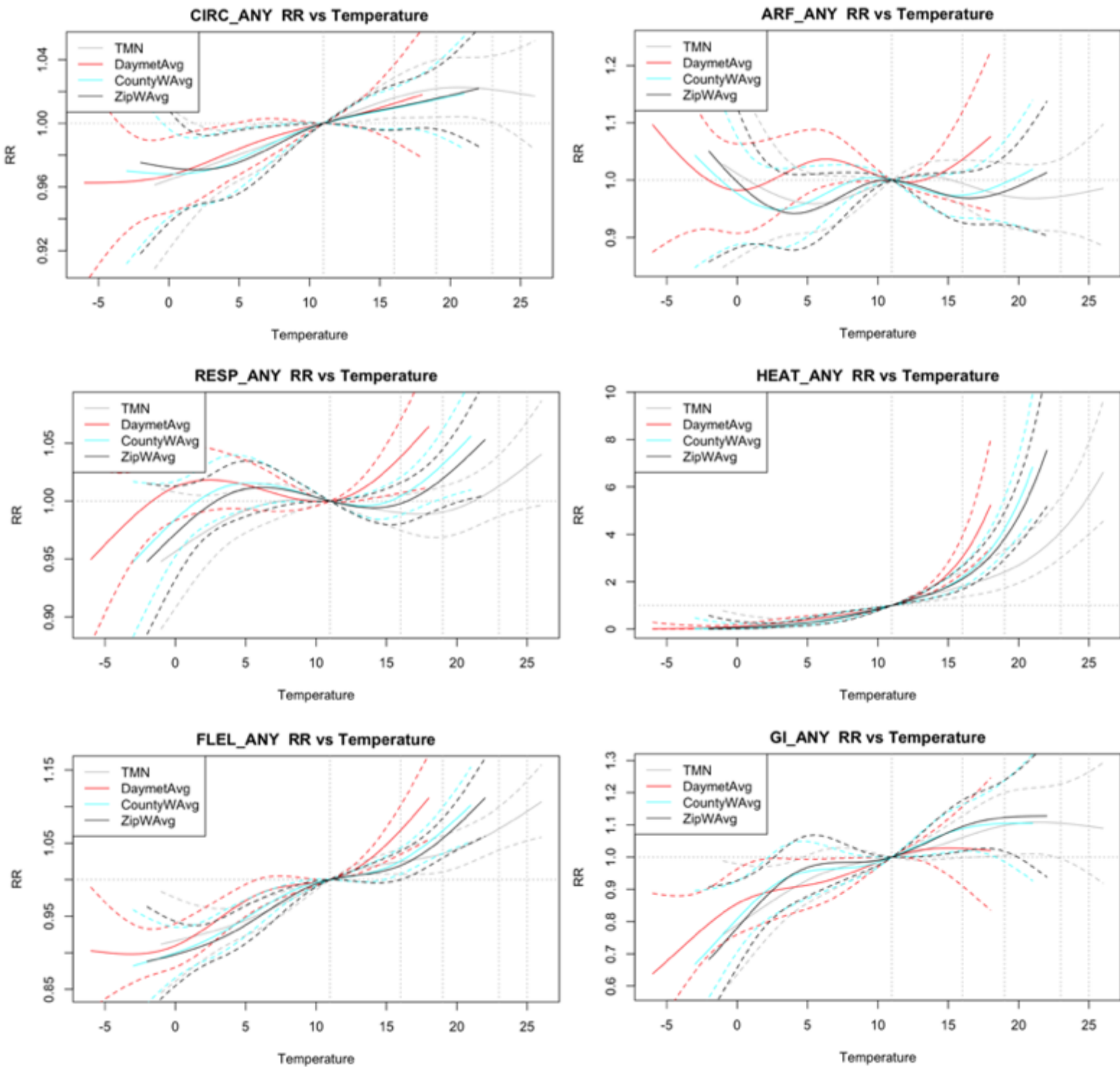


Figure 9. Relative risk of selected health outcomes vs maximum temperature during May to September in Newark, 2005-2016

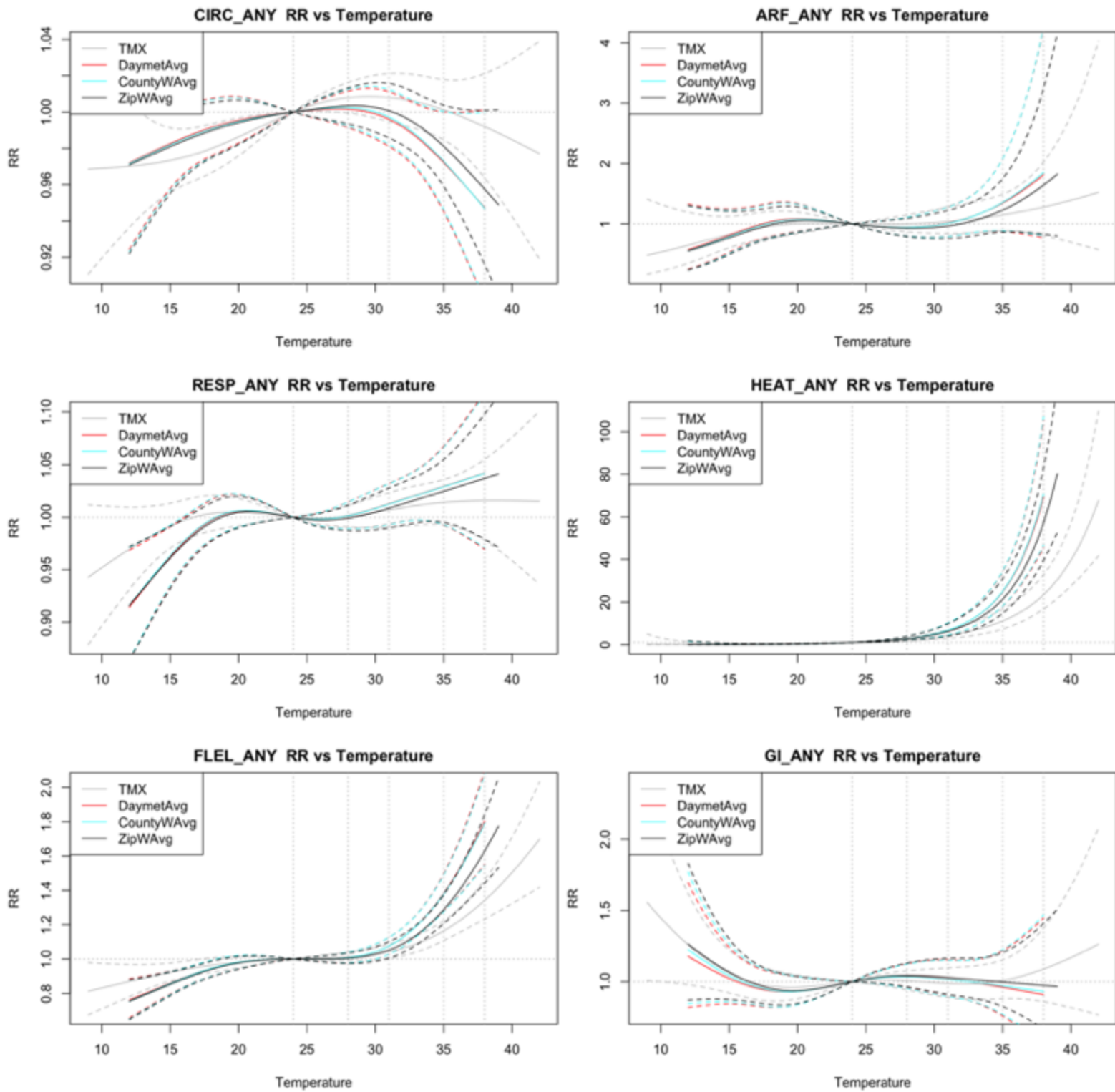


Figure 10. Relative risk of selected health outcomes vs minimum temperature during May to September in Newark, 2005-2016

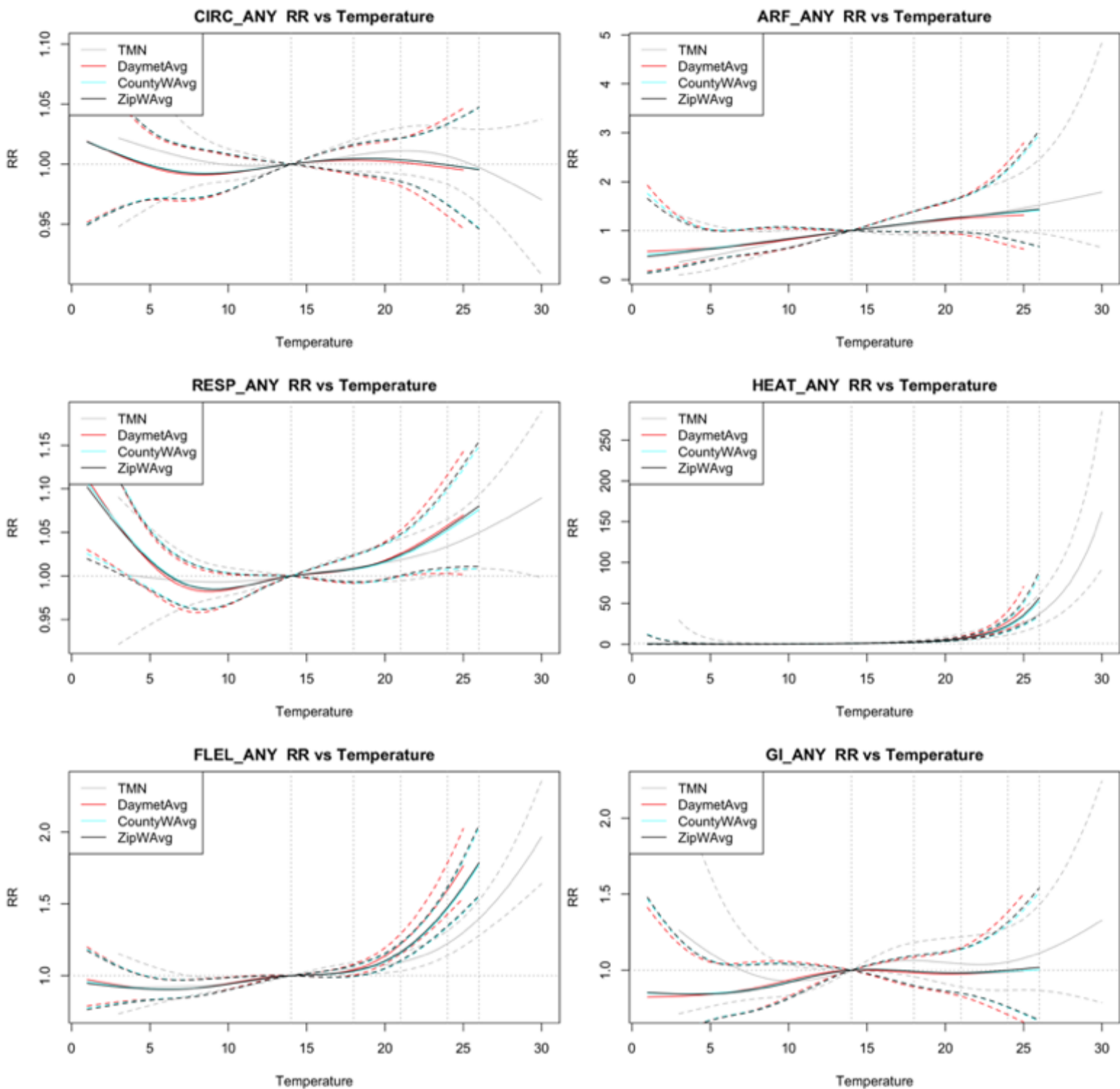


Figure 11. Relative risk of selected health outcomes vs maximum temperature during May to September in Phoenix, 2008-2016

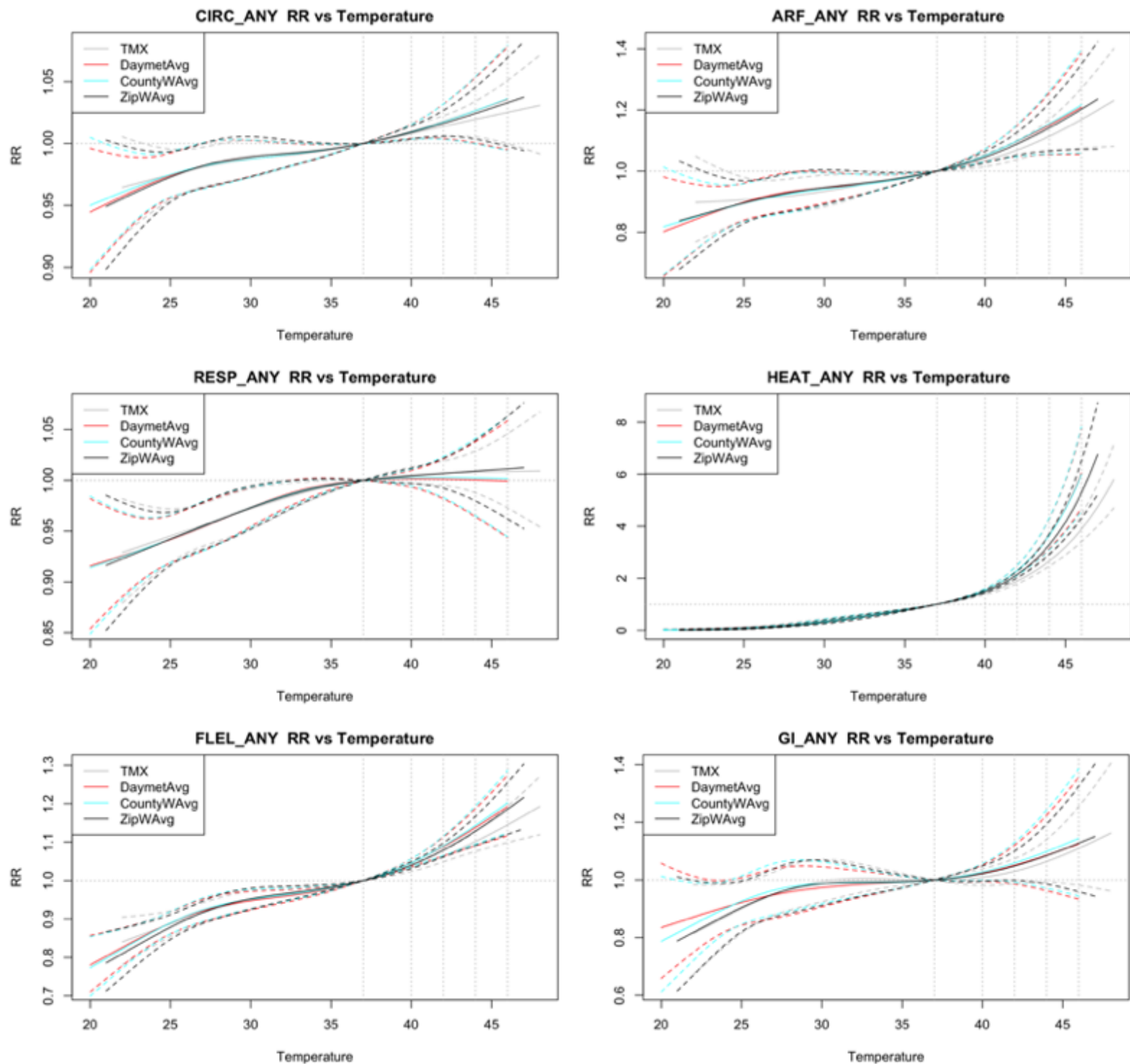
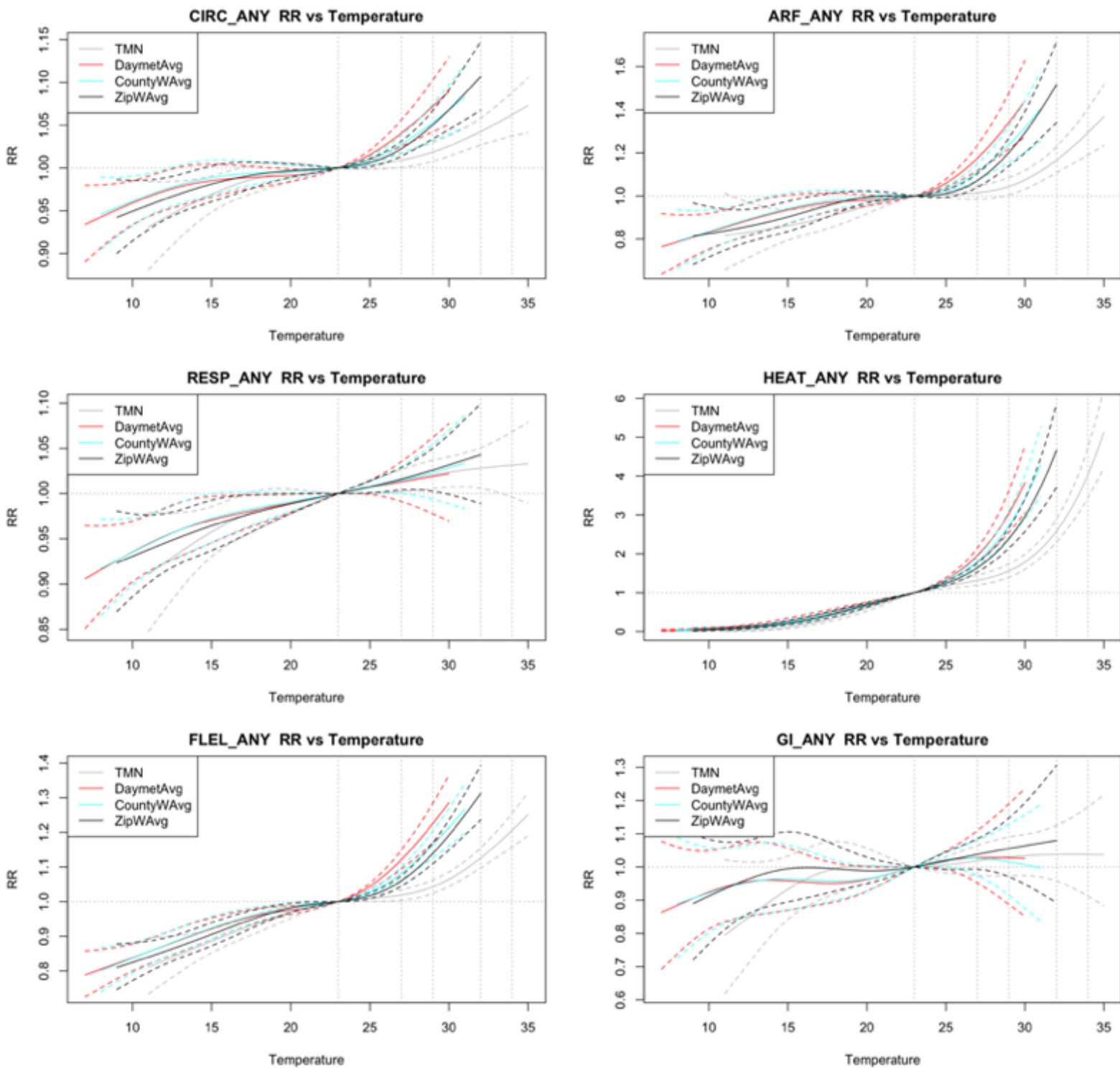


Figure 12. Relative risk of selected health outcomes vs minimum temperature during May to September in Phoenix, 2008-2016





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