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Supplementary Information for

Public perceptions of the health risks of extreme heat across U.S. states, counties, and neighborhoods

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Supporting Information Text

Survey details. The survey data were collected via the GfK Knowledgepanel, a U.S. national probability-based online panel. Panel members are recruited by telephone using random digit dial probability sampling methods and persons recruited who do not have internet access are provided access by GfK. Questions were included on the Knowledgepanel Omnibus survey, a shared-cost national survey that includes questions from multiple clients and is conducted weekly with a sample of 1000 U.S. adults (age 18 and over). Our survey items were included on 10 survey waves every two weeks, beginning on 13 June 2015 and concluding on 17 October 2015 (Table S1). Each wave was fielded for three days.

We included nine questions measuring heat risk perceptions, composed of three questions and three sub-questions. Questions were designed to measure three constructs related to heat risk perception: perceived probability of harm, perceived severity of harm, and worry or concern about the hazard. Responses to each question were indicated with a labeled slider bar on a 0-100 scale, with labels placed at 0, 25, 50, 75, and 100. Respondents could answer by moving the slider to any integer on the scale. In addition to the slider bar, Question 1 also included a separate response option for "Will not be harmed because a heat wave will not occur." Questions were as follows:

1. A heat wave is a period of unusually and uncomfortably hot weather. Thinking about your local area, how likely is it, if at all, that each of the following will be harmed by a heat wave in the next five years? If you're not sure, just give your best estimate.

A. Your health [Definitely will not be harmed; About a 25% chance of harm; About a 50-50 chance of harm; About a 75% chance of harm; Definitely will be harmed]

B. The health of others in your family [Definitely will not be harmed; About a 25% chance of harm; About a 50-50 chance of harm; About a 75% chance of harm; Definitely will be harmed]

C. The health of others in your community [Definitely will not be harmed; About a 25% chance of harm; About a 50-50 chance of harm; About a 75% chance of harm; Definitely will be harmed]

2. If a heat wave were to occur in your local area, how much, if at all, do you think it would harm the following?

A. Your health [Would cause no harm at all; A little harm; Moderate harm; A great deal of harm; Would cause extreme harm]

B. The health of others in your family [Would cause no harm at all; A little harm; Moderate harm; A great deal of harm; Would cause extreme harm]

C. The health of others in your community [Would cause no harm at all; A little harm; Moderate harm; A great deal of harm; Would cause extreme harm]

3. How worried, if at all, are you about the effects of heat waves on the following?

A. Your health [Not worried at all; A little worried; Moderately worried; Very worried; Extremely worried]

B. The health of others in your family [Not worried at all; A little worried; Moderately worried; Very worried; Extremely worried]

A. The health of others in your community [Not worried at all; A little worried; Moderately worried; Very worried; Extremely worried]

Model development. Although there is a strong theoretical basis for selecting several sociodemographic factors in a model of heat wave risk perceptions, census and other datasets provide many different measures of most factors. We used Random Forest (RF) analysis to identify potential predictors for inclusion in our model. RF ranks variables by their predictive importance, which we compared for four indices including personal harm, harm to one's family, and community harm, and an overall risk perception index that combined these three, resulting in four indices. We also compared the RF results for both binary and continuous outcomes, resulting in a total of eight indices. Age, race/ethnicity, education, disability, various measures of income, temperature, and the proportion of impervious surfaces in the tract consistently ranked among the top ten predictors in the RF analysis. Model selection proceeded by comparing predictions and errors across the reduced variable sets identified from the RF analysis.

A. Model specification.

We specify our model as follows, predicting heat risk perceptions (y) for each individual i:

$$y_i \sim N\left(\gamma^0 + \alpha^{\text{race}}_{j[i]} + \alpha^{\text{age}}_{k[i]} + \alpha^{\text{gender}}_{l[i]} + \alpha^{\text{race.age.gender}}_{j[i],k[i],l[i]} + \alpha^{\text{tract}}_{t[i]}, \sigma_y^2\right),$$

where

$$\alpha_j^{\text{race}} \sim N(0, \sigma^2_{\text{race}}) \text{ for } j = 1, ..., 5$$
$$\alpha_k^{\text{age}} \sim N(0, \sigma^2_{\text{age}}) \text{ for } k = 1, ..., 10$$
$$\alpha_l^{\text{gender}} \sim N(0, \sigma^2_{\text{gender}}) \text{ for } l = 1, 2$$
$$\alpha_{j,k,l}^{\text{race.age.gender}} \sim N(0, \sigma^2_{\text{race.age.gender}}) \text{ for}$$
$$j = 1, ...5;\ k = 1, ...10;\ l = 1, 2$$
$$\alpha_t^{\text{tract}} \sim N(\alpha^{\text{region}}_{r[t]} + \alpha^{\text{state}}_{s[t]} + \alpha^{\text{county}}_{c[t]} + \gamma^{\text{tmean}}\text{tmean}_t +$$
$$\gamma^{\text{landcover}}\text{landcover}_t + \gamma^{\text{education}}\text{education}_t + \gamma^{\text{lowincome}}\text{lowincome}_t$$
$$+\gamma^{\text{disability65}}\text{disability65}_t, \sigma^2_{\text{tract}}) \text{ for } t = 1, ..., 6994$$
$$\alpha_r^{\text{division}} \sim N(0, \sigma^2_{\text{division}}) \text{ for } r = 1, ..., 9$$
$$\alpha_s^{\text{state}} \sim N(0, \sigma^2_{\text{state}}) \text{ for } s = 1, ..., 51$$
$$\alpha_c^{\text{county}} \sim N(0, \sigma^2_{\text{county}}) \text{ for } c = 1, ..., 1524$$

Model validation surveys. We conducted two additional sets of independent surveys to validate our model estimates. One set of surveys was targeted to the state level, while the other was targeted to the census tract level.

The state-level surveys were conducted using Google Consumer Surveys, an online survey tool that can sample the Internet-using population at relatively low cost compared to telephone, mail, or Internet panel survey methods. GCS samples Internet users on sites that are part of Google's advertising network, such as local newspapers. In a typical use case, respondents may opt to answer one to ten survey questions to access site content instead of purchasing the content or viewing ads. Survey weights are applied based on census Current Population Survey frequencies for respondents' inferred demographic categories, including age, gender, and location. This platform has been show to achieve similar accuracy to traditional survey research techniques (1–3).

For the state-level surveys, eight states were selected by stratifying all 50 states and the District of Columbia into population quartiles, and randomly selecting two states within each quartile. Selected states were Indiana, Minnesota, New Mexico, Oklahoma, Pennsylvania, Rhode Island, South Carolina, and Washington. We targeted a sample of at least 500 respondents in each selected state. Surveys were fielded in May and June 2016.

The state-level validation surveys were conducted using a single question (analogous to question 1A in our primary survey), which we adapted for Google Consumer Surveys' word limit and response option format:

1. A heat wave is a period of unusually and uncomfortably hot weather. If a heat wave were to occur in your area, how much, if at all, do you think it would harm your health? [No harm at all; A little harm; Moderate harm; A great deal of harm; Extreme harm]

Compared against these state-level surveys, the mean absolute error of our MRP model estimates was 1.6 points, and the correlation of the model estimates to the state-level survey results was r=0.82 (Fig. S1).

Our second set of validation surveys was conducted at the census tract level. The tract-level surveys were conducted via a combined mail and online design following the Tailored Design Method (4). Tracts were selected by stratifying all U.S. counties with heat-related mortality statistics recorded in the CDC WONDER database into those with above- and below-average per capita mortality and above- and below-average risk perceptions. One county was then randomly selected from each of the two groups that had higher-than-average heat-related deaths and either lower- or higher-than average risk perceptions. That is, one county had high heat-related deaths and higher-than-average risk perceptions (Imperial County, CA), and the other had high heat-related deaths and lower-than-average risk perceptions (Peoria County, IL). One census tract was then randomly selected within each of the two counties. Mailing addresses were then randomly sampled within each tract. Of 3600 total mailing addresses sampled, we received 756 completed surveys, for an overall response rate of 21%. Respondents were first contacted to participate in the online survey via postal mail, which included a 2 dollar incentive. Nonrespondents were sent reminders and paper versions of the survey, with up to two reminders and paper surveys mailed. The surveys were provided in both English and Spanish. The tract-level surveys replicated the survey questionnaire wording from the primary national survey, with supplementary demographic questions and several related questions on behaviors and experiences related to heat waves following the risk perception items. The tract-level surveys were fielded in July-September 2016.

Comparing heat risk perceptions to heat mortality statistics. Heat-related mortality data are available at the state level (5), which allows for a comparison between recent mortality and risk perception estimates. There is a positive relationship between risk perception and mortality from 1999-2015 (Supplementary Fig. 2) (r=0.57). Most states in the South have higher risk perceptions than would be predicted by their per capita mortality, while most states in the Midwest have lower risk perceptions than would be predicted by their mortality rate. These patterns may indicate adaptation in states with high risk perceptions and lower than expected mortality. For example, the heat risk perception index is 10 points higher in California than Wisconsin, yet mortality is similar in the two states (0.2 per 100,000) despite greater population exposure to extreme heat in California. Similarly, mortality is comparable between Texas and Kansas (0.3 per 100,000), yet the heat risk perception index is 7.5 points higher in Texas.

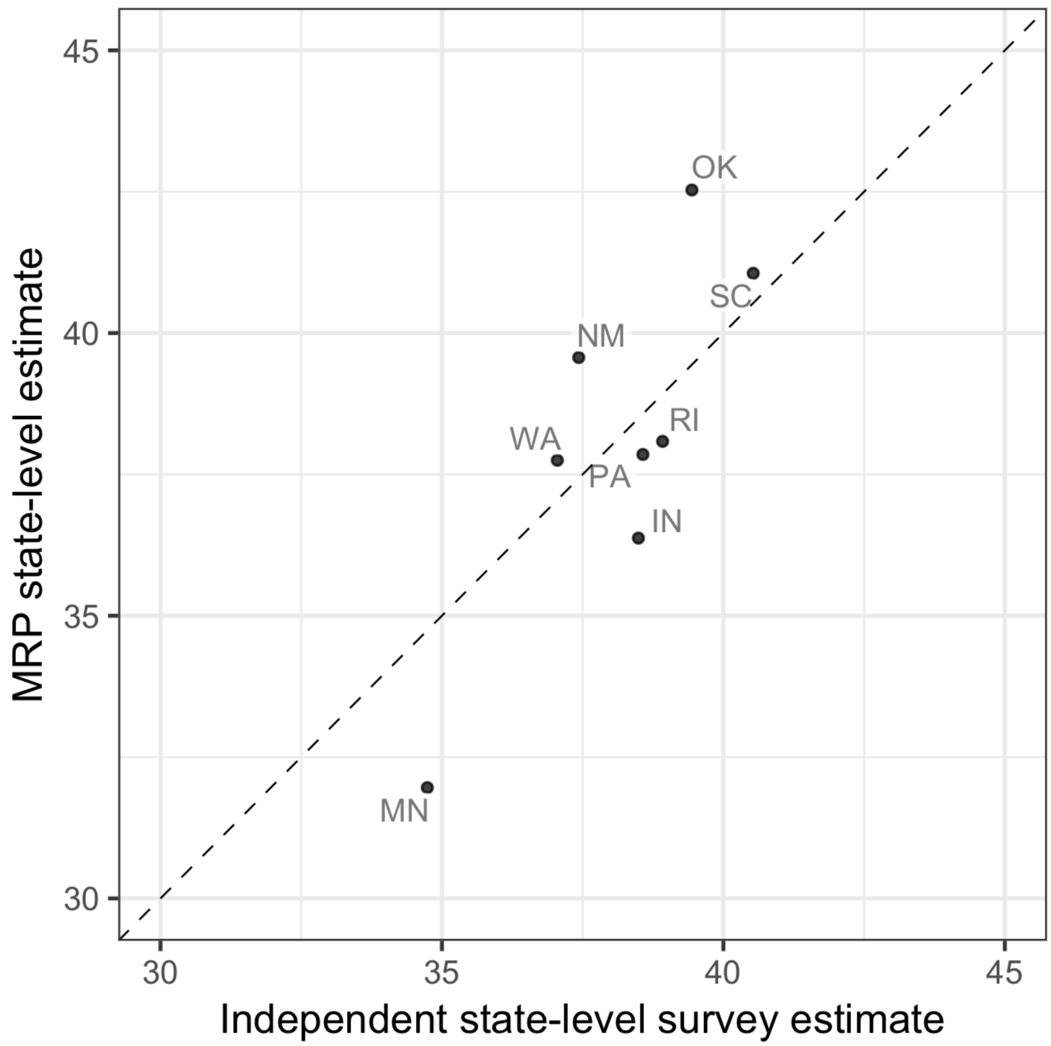

Fig. S1. External validation comparison of estimated risk perception index with mean-centered independent survey estimates in eight randomly selected states. The mean absolute difference between MRP model estimates and the external survey results was 1.6 points. Estimates were correlated at r=0.82.

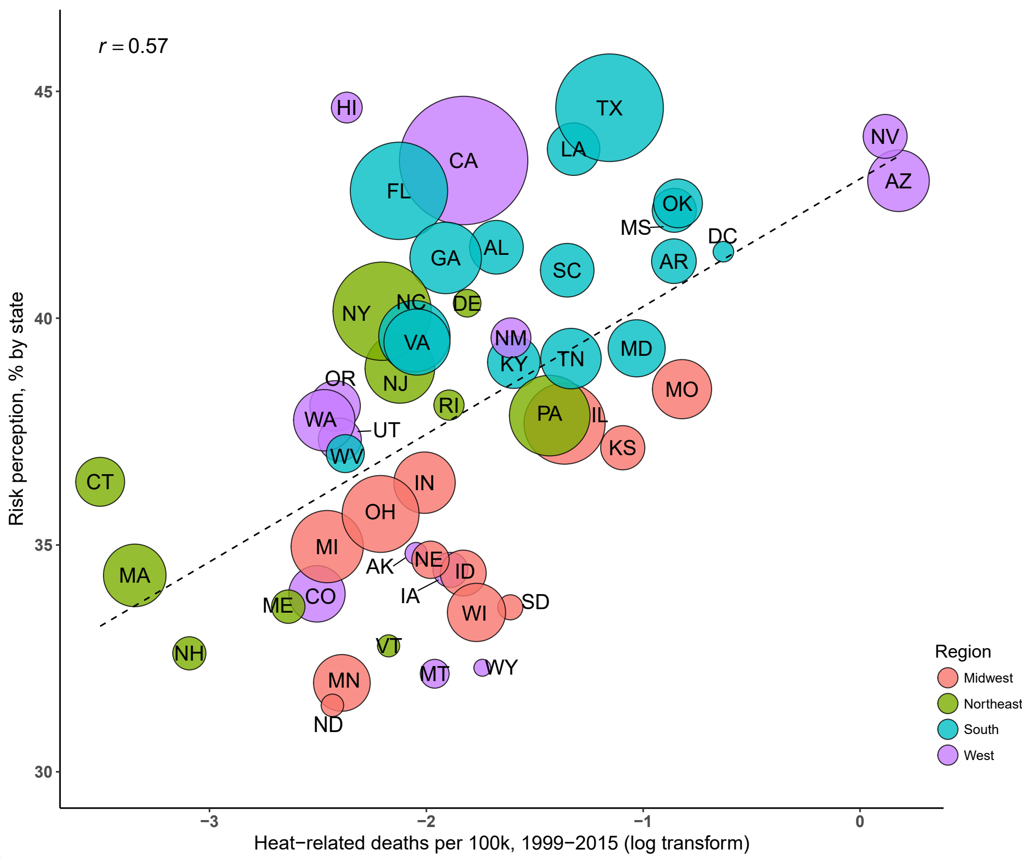

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Fig. S2. Risk perception as compared to heat-related mortality (MCD-ICD 10 code T67) at the state level, 1999-2015 (5).

Table S1. National survey dates

Wave	Survey dates
1.	12-14 June 2015
2.	26-28 June 2015
3.	10-12 July 2015
4.	24-26 July 2015
5.	7-9 August 2015
6.	21-23 August 2015
7.	4-6 September 2015
8.	18-20 September 2015
9.	2-4 October 2015
10.	16-18 October 2015

Table S2. Multilevel regression model tract-level fixed effects conditional point estimates and standard errors

	Fixed effect coefficient:	
	Scaled	Unscaled
Mean daily summer (JJA) temperature (ºC)	2.698	0.519
	(0.429)	(0.082)
Mean percent impervious surface	1.101	0.051
	(0.372)	(0.017)
Percent of adult pop. with bachelors degree or higher	−1.158	−0.064
	(0.424)	(0.023)
Percent of adult pop. receiving SNAP benefits	1.553	0.147
	(0.517)	(0.049)
Percent of pop. age 65 and over with disability status	0.236	0.020
	(0.366)	(0.031)
Intercept	41.653	
	(2.377)	

Note: Standard errors in parentheses. Scaled variables have been mean-centered and divided by their standard deviations.

Table S3. Modeled conditional point estimates and standard errors for age random effect

	Intercept	Std. error
18-19 years	−0.669	0.831
20-24 years	−0.311	0.686
25-29 years	−0.039	0.692
30-34 years	−0.236	0.684
35-44 years	−1.300	0.595
45-54 years	0.509	0.618
55-64 years	1.296	0.593
65-74 years	0.633	0.662
75-84 years	0.247	0.804
85 years and over	−0.129	0.946

Table S4. Modeled conditional point estimates and standard errors for race/ethnicity random effect

	Intercept	Std. error
2+ Races, Non-Hispanic	-0.478	1.516
Black, Non-Hispanic	0.292	1.322
Hispanic or Latino/a	0.792	1.279
Other, Non-Hispanic	3.361	1.450
White, Non-Hispanic	-3.966	1.116

Table S5. Modeled conditional point estimates and standard errors for gender random effect

	Intercept	Std. error
Female	2.379	1.176
Male	−2.379	1.179

Table S6. Modeled conditional point estimates and standard errors for gender by race/ethnicity by age interaction random effect

	Intercept	Std. error
Female:2+ Races, Non-Hispanic:18-19 years	0.003	0.156
Female:2+ Races, Non-Hispanic:20-24 years	-0.002	0.156
Female:2+ Races, Non-Hispanic:25-29 years	-0.003	0.156
Female:2+ Races, Non-Hispanic:30-34 years	-0.001	0.156
Female:2+ Races, Non-Hispanic:35-44 years	-0.003	0.156
Female:2+ Races, Non-Hispanic:45-54 years	-0.003	0.156
Female:2+ Races, Non-Hispanic:55-64 years	0.001	0.156
Female:2+ Races, Non-Hispanic:65-74 years	-0.001	0.156
Female:2+ Races, Non-Hispanic:75-84 years	-0.0003	0.156
Female:Black, Non-Hispanic:18-19 years	0.001	0.156
Female:Black, Non-Hispanic:20-24 years	-0.003	0.156
Female:Black, Non-Hispanic:25-29 years	0.0001	0.156
Female:Black, Non-Hispanic:30-34 years	-0.007	0.156
Female:Black, Non-Hispanic:35-44 years	-0.010	0.156
Female:Black, Non-Hispanic:45-54 years	0.011	0.156
Female:Black, Non-Hispanic:55-64 years	0.001	0.156
Female:Black, Non-Hispanic:65-74 years	0.004	0.156
Female:Black, Non-Hispanic:75-84 years	0.003	0.156
Female:Hispanic:18-19 years	-0.003	0.156
Female:Hispanic:20-24 years	-0.014	0.156
Female:Hispanic:25-29 years	-0.002	0.156
Female:Hispanic:30-34 years	-0.012	0.156
Female:Hispanic:35-44 years	-0.011	0.156
Female:Hispanic:45-54 years	0.002	0.156
Female:Hispanic:55-64 years	0.007	0.156
Female:Hispanic:65-74 years	0.012	0.156
Female:Hispanic:85 years and over	-0.001	0.156
Female:Other, Non-Hispanic:18-19 years	-0.004	0.156
Female:Other, Non-Hispanic:20-24 years	0.014	0.156
Female:Other, Non-Hispanic:25-29 years	0.004	0.156
Female:Other, Non-Hispanic:30-34 years	0.001	0.156
Female:Other, Non-Hispanic:35-44 years	-0.004	0.156
Female:Other, Non-Hispanic:45-54 years	-0.0002	0.156
Female:Other, Non-Hispanic:55-64 years	0.001	0.156
Female:Other, Non-Hispanic:65-74 years	-0.009	0.156
Female:Other, Non-Hispanic:75-84 years	-0.0001	0.156
Female:White, Non-Hispanic:18-19 years	-0.013	0.156
Female:White, Non-Hispanic:20-24 years	0.012	0.156
Female:White, Non-Hispanic:25-29 years	0.009	0.156
Female:White, Non-Hispanic:30-34 years	0.005	0.156
Female:White, Non-Hispanic:35-44 years	-0.024	0.155
Female:White, Non-Hispanic:45-54 years	-0.004	0.155
Female:White, Non-Hispanic:55-64 years	0.024	0.155
Female:White, Non-Hispanic:65-74 years	0.015	0.155
Female:White, Non-Hispanic:75-84 years	0.010	0.156
Female:White, Non-Hispanic:85 years and over	0.002	0.156
Male:2+ Races, Non-Hispanic:18-19 years	0.001	0.156
Male:2+ Races, Non-Hispanic:20-24 years	0.001	0.156
Male:2+ Races, Non-Hispanic:25-29 years	0.001	0.156
Male:2+ Races, Non-Hispanic:30-34 years	0.002	0.156
Male:2+ Races, Non-Hispanic:35-44 years	-0.001	0.156
Male:2+ Races, Non-Hispanic:45-54 years	0.009	0.156
Male:2+ Races, Non-Hispanic:55-64 years	-0.007	0.156
Male:2+ Races, Non-Hispanic:65-74 years	0.001	0.156
Male:2+ Races, Non-Hispanic:75-84 years	0.001	0.156
Male:Black, Non-Hispanic:18-19 years	-0.005	0.156
Male:Black, Non-Hispanic:20-24 years	-0.003	0.156
Male:Black, Non-Hispanic:25-29 years	0.010	0.156

	Intercept	Std. error
Male:Black, Non-Hispanic:30-34 years	-0.008	0.156
Male:Black, Non-Hispanic:35-44 years	-0.007	0.156
Male:Black, Non-Hispanic:45-54 years	0.018	0.156
Male:Black, Non-Hispanic:55-64 years	-0.007	0.156
Male:Black, Non-Hispanic:65-74 years	0.002	0.156
Male:Black, Non-Hispanic:75-84 years	0.002	0.156
Male:Black, Non-Hispanic:85 years and over	-0.002	0.156
Male:Hispanic:18-19 years	-0.002	0.156
Male:Hispanic:20-24 years	0.001	0.156
Male:Hispanic:25-29 years	0.010	0.156
Male:Hispanic:30-34 years	0.011	0.156
Male:Hispanic:35-44 years	0.001	0.156
Male:Hispanic:45-54 years	-0.003	0.156
Male:Hispanic:55-64 years	0.006	0.156
Male:Hispanic:65-74 years	0.002	0.156
Male:Hispanic:75-84 years	-0.001	0.156
Male:Other, Non-Hispanic:18-19 years	-0.007	0.156
Male:Other, Non-Hispanic:20-24 years	0.005	0.156
Male:Other, Non-Hispanic:25-29 years	0.002	0.156
Male:Other, Non-Hispanic:30-34 years	-0.005	0.156
Male:Other, Non-Hispanic:35-44 years	0.013	0.156
Male:Other, Non-Hispanic:45-54 years	0.001	0.156
Male:Other, Non-Hispanic:55-64 years	-0.001	0.156
Male:Other, Non-Hispanic:65-74 years	-0.001	0.156
Male:Other, Non-Hispanic:75-84 years	-0.000	0.156
Male:White, Non-Hispanic:18-19 years	0.012	0.156
Male:White, Non-Hispanic:20-24 years	-0.020	0.156
Male:White, Non-Hispanic:25-29 years	-0.032	0.156
Male:White, Non-Hispanic:30-34 years	0.008	0.156
Male:White, Non-Hispanic:35-44 years	0.013	0.155
Male:White, Non-Hispanic:45-54 years	-0.018	0.155
Male:White, Non-Hispanic:55-64 years	0.008	0.155
Male:White, Non-Hispanic:65-74 years	-0.008	0.155
Male:White, Non-Hispanic:75-84 years	-0.009	0.156
Male:White, Non-Hispanic:85 years and over	-0.003	0.156

Table S7. Modeled conditional point estimates and standard errors for census division random effect

	Intercept	Std. error
East-North Central	-1.279	0.852
East-South Central	0.221	1.047
Mid-Atlantic	0.356	0.907
Mountain	-0.691	0.998
New England	-0.792	1.082
Pacific	2.625	0.935
South Atlantic	0.500	0.812
West-North Central	-1.499	0.960
West-South Central	0.557	0.964

Table S8. Modeled conditional point estimates and standard errors for state random effect

StateFP	State_name	Intercept	Std. error
01	Alabama	0.238	0.764
02	Alaska	-0.101	0.792
04	Arizona	-0.200	0.761
05	Arkansas	0.086	0.771
06	California	0.388	0.709
08	Colorado	-0.158	0.759
09	Connecticut	0.167	0.771
10	Delaware	0.207	0.786
11	District of Columbia	0.019	0.790
12	Florida	-0.402	0.691
13	Georgia	0.028	0.726
15	Hawaii	-0.016	0.789
16	Idaho	0.037	0.779
17	Illinois	0.175	0.727
18	Indiana	0.321	0.748
19	Iowa	0.069	0.766
20	Kansas	-0.280	0.770
21	Kentucky	-0.049	0.762
22	Louisiana	0.165	0.765
23	Maine	0.127	0.781
24	Maryland	-0.043	0.753
25	Massachusetts	-0.557	0.756
26	Michigan	-0.422	0.722
27	Minnesota	-0.423	0.744
28	Mississippi	0.149	0.776
29	Missouri	0.521	0.752
30	Montana	0.082	0.788
31	Nebraska	-0.324	0.774
32	Nevada	0.108	0.780
33	New Hampshire	-0.120	0.785
34	New Jersey	-0.120	0.740
35	New Mexico	0.033	0.780
36	New York	-0.169	0.715
37	North Carolina	-0.231	0.726
38	North Dakota	-0.060	0.788
39	Ohio	-0.190	0.715
40	Oklahoma	-0.036	0.770
41	Oregon	0.042	0.763
42	Pennsylvania	0.387	0.715
44	Rhode Island	0.132	0.789
45	South Carolina	0.046	0.759
46	South Dakota	0.085	0.788
47	Tennessee	-0.277	0.758
48	Texas	-0.062	0.719
49	Utah	-0.052	0.769
50	Vermont	0.035	0.791
51	Virginia	0.687	0.725
53	Washington	0.409	0.748
54	West Virginia	-0.174	0.777
55	Wisconsin	-0.235	0.735
56	Wyoming	-0.041	0.794

Tract-level maps for 20 largest counties by population.

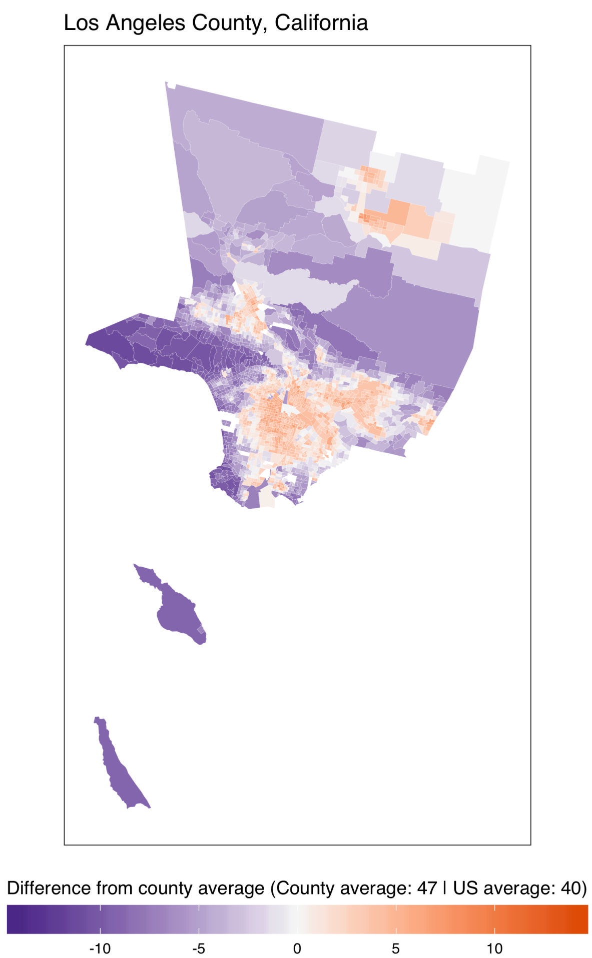

Fig. S3. Tract level estimates of heat risk perception for Los Angeles County, CA. Tracts are shaded by the difference from the average for the county.

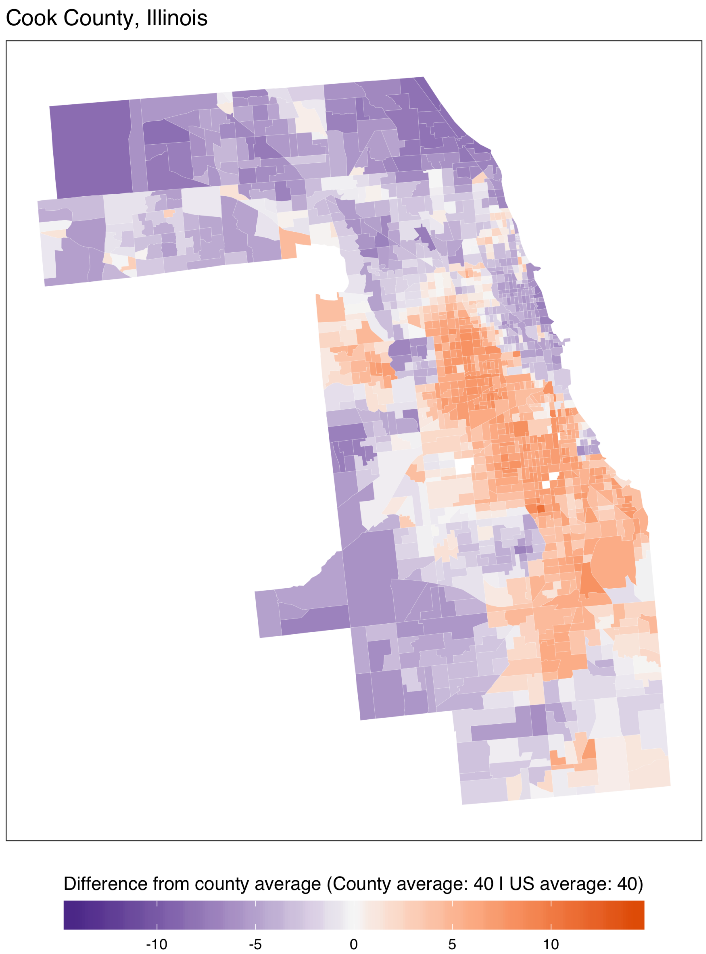

Fig. S4. Tract level estimates of heat risk perception for Cook County, IL. Tracts are shaded by the difference from the average for the county.

Harris County, Texas

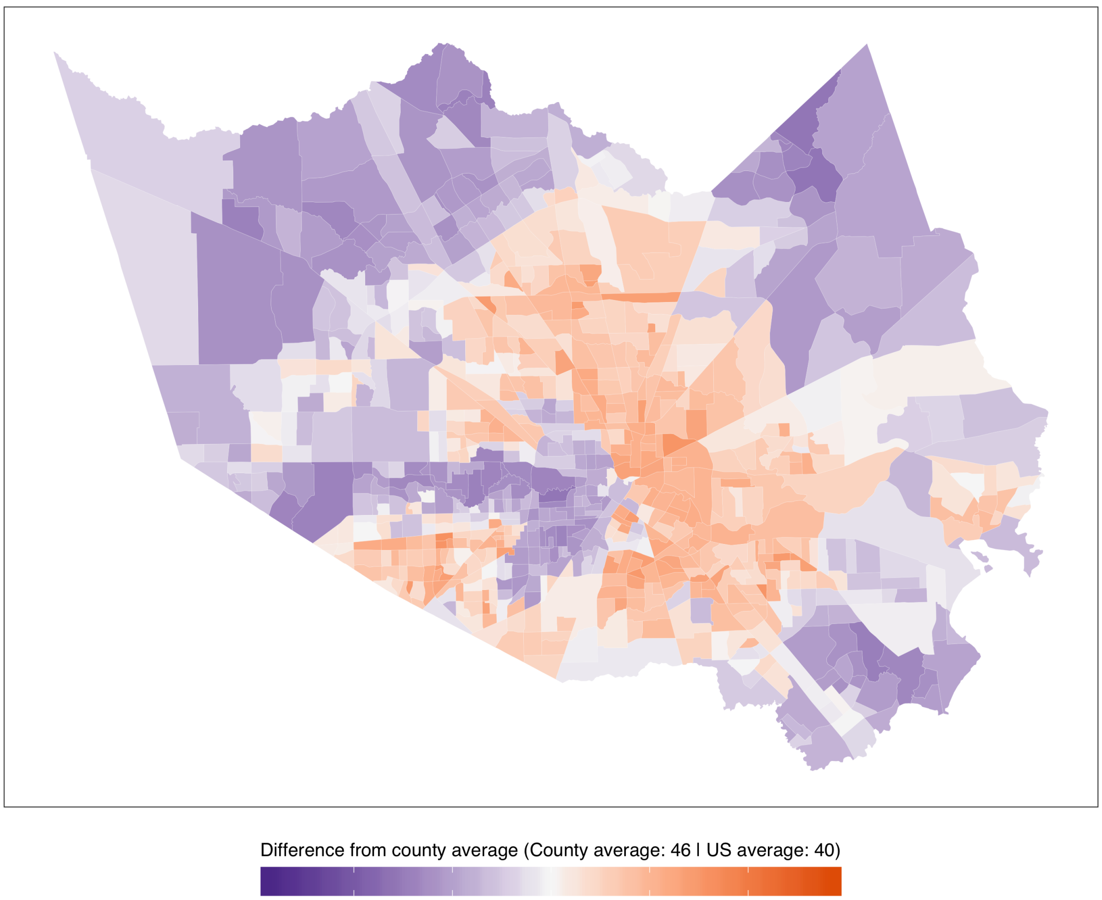

Fig. S5. Tract level estimates of heat risk perception for Harris County, TX. Tracts are shaded by the difference from the average for the county.

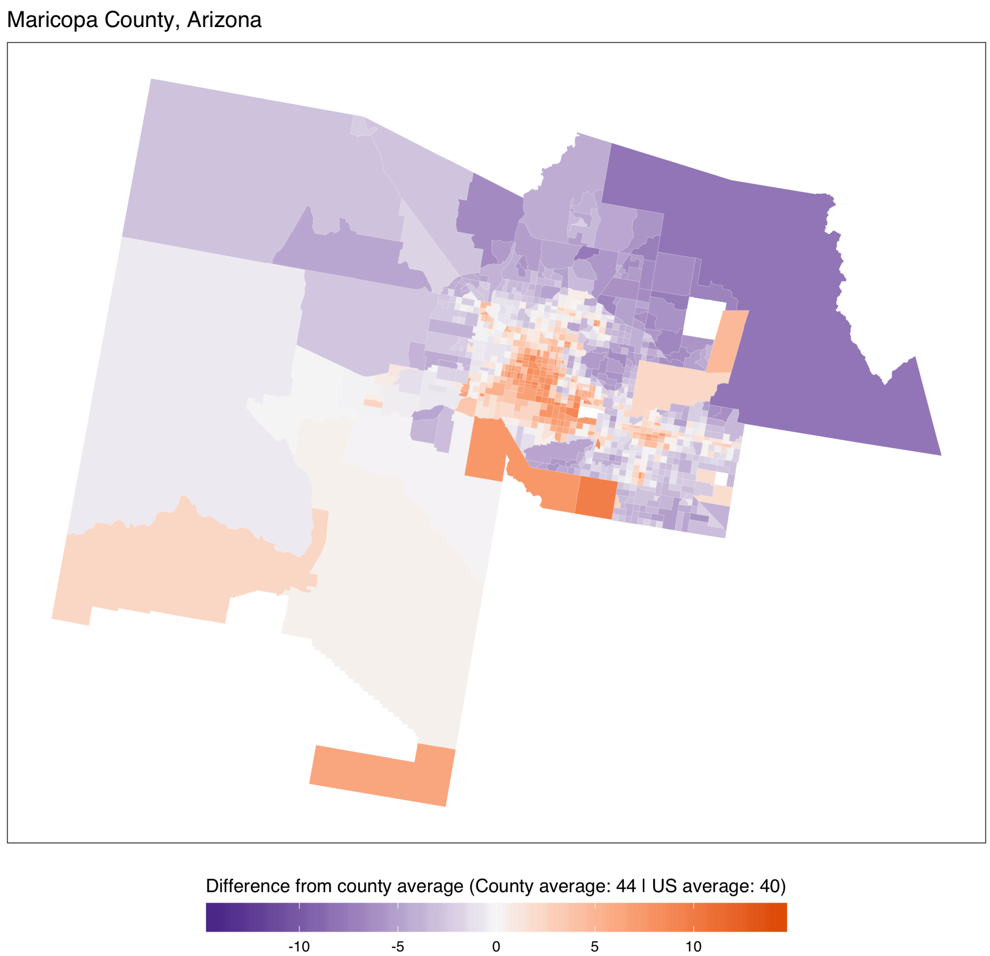

Fig. S6. Tract level estimates of heat risk perception for Maricopa County, AZ. Tracts are shaded by the difference from the average for the county.

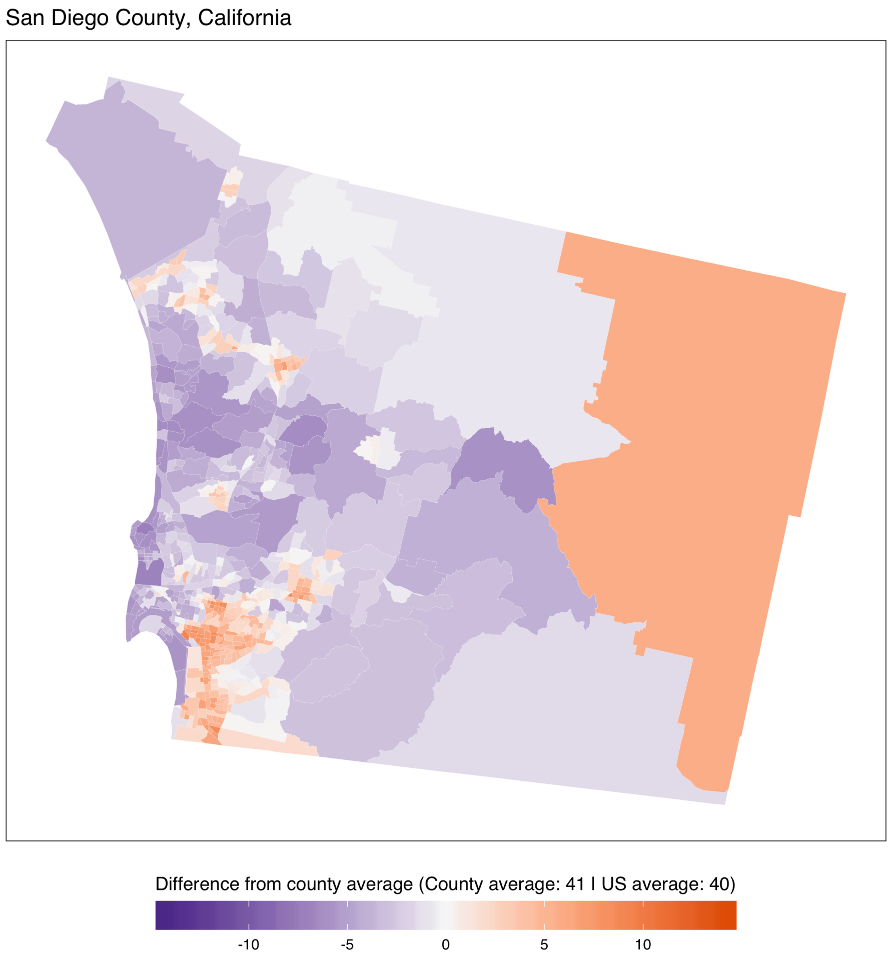

Fig. S7. Tract level estimates of heat risk perception for San Diego County, CA. Tracts are shaded by the difference from the average for the county.

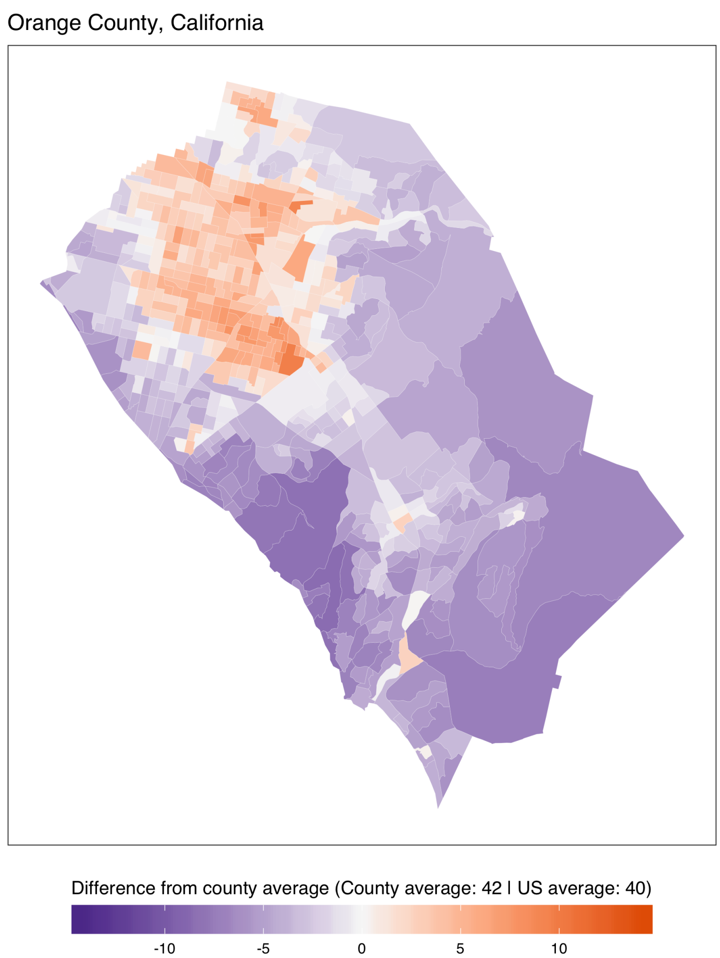

Fig. S8. Tract level estimates of heat risk perception for Orange County, CA. Tracts are shaded by the difference from the average for the county.

Miami-Dade County, Florida

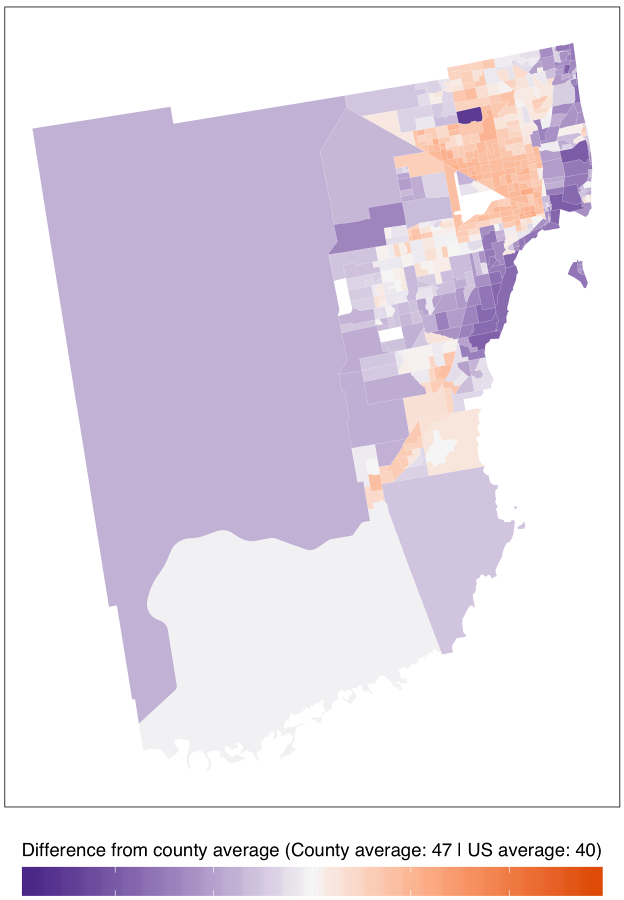

Fig. S9. Tract level estimates of heat risk perception for Miami-Dade County, FL. Tracts are shaded by the difference from the average for the county.

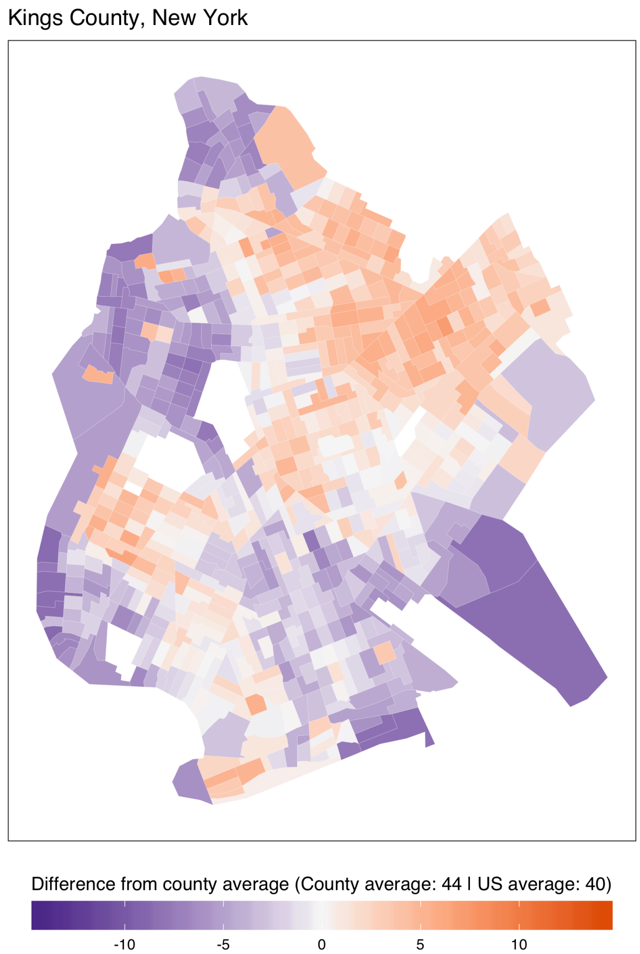

Fig. S10. Tract level estimates of heat risk perception for Kings County, NY. Tracts are shaded by the difference from the average for the county.

Dallas County, Texas

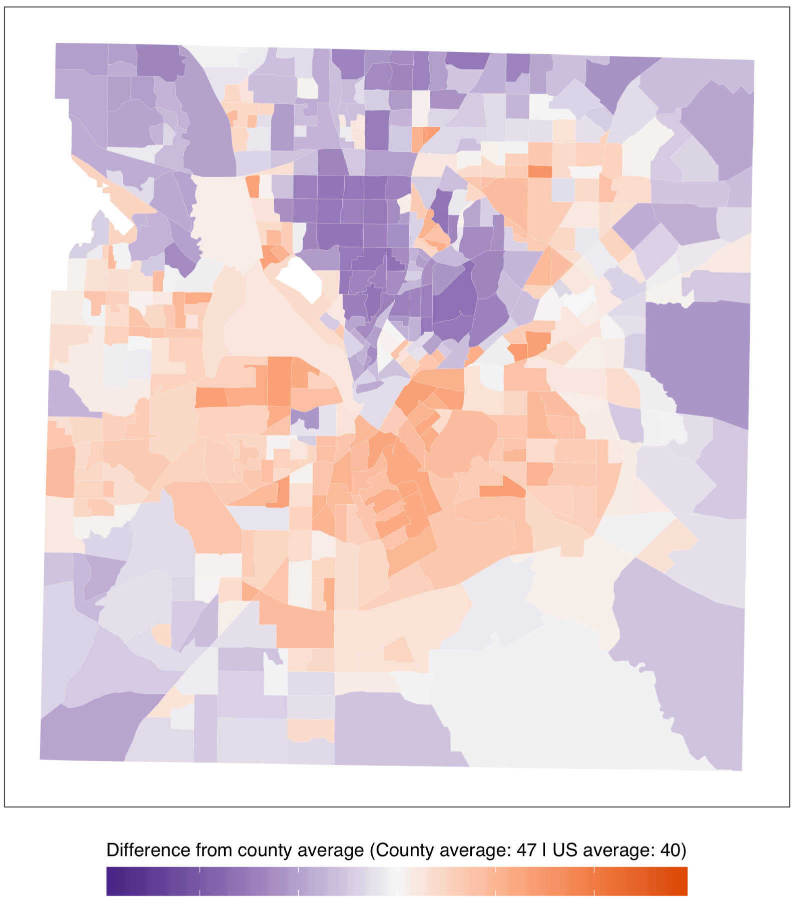

Fig. S11. Tract level estimates of heat risk perception for Dallas County, TX. Tracts are shaded by the difference from the average for the county.

Riverside County, California

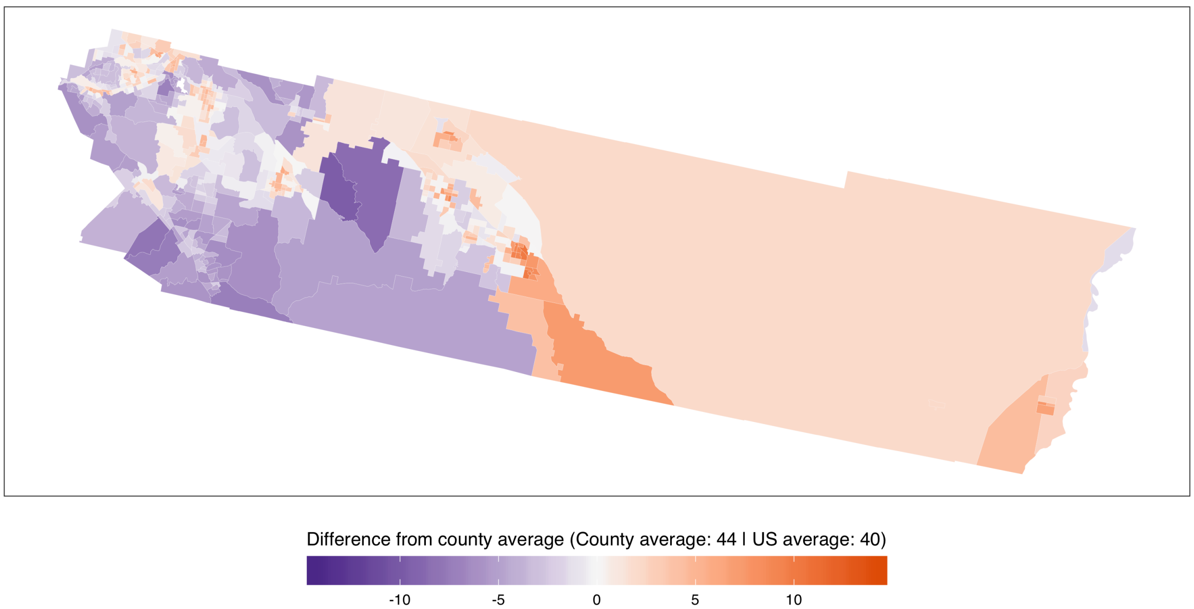

Fig. S12. Tract level estimates of heat risk perception for Riverside County, CA. Tracts are shaded by the difference from the average for the county.

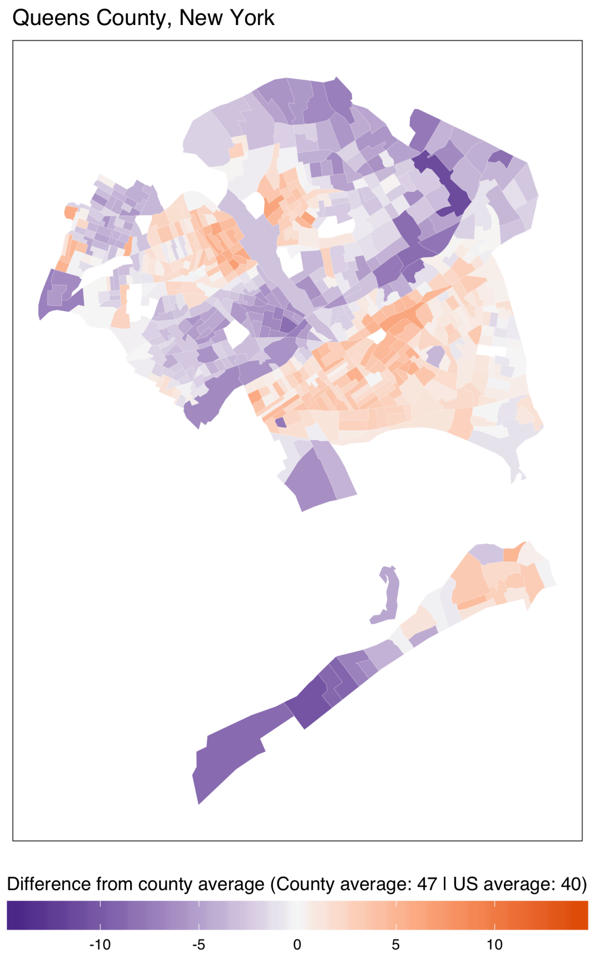

Fig. S13. Tract level estimates of heat risk perception for Queens County, NY. Tracts are shaded by the difference from the average for the county.

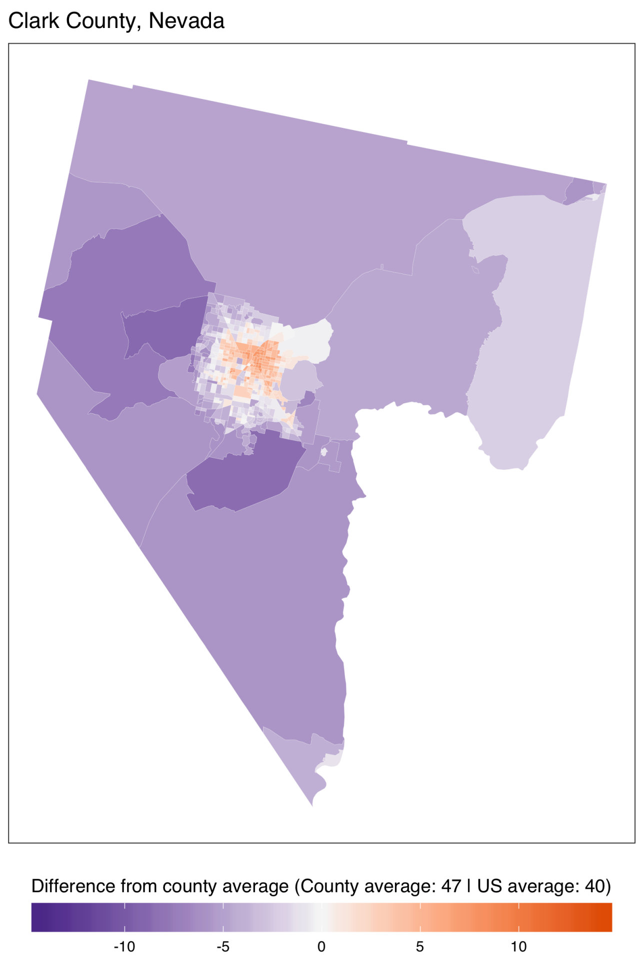

Fig. S14. Tract level estimates of heat risk perception for Clark County, NV. Tracts are shaded by the difference from the average for the county.

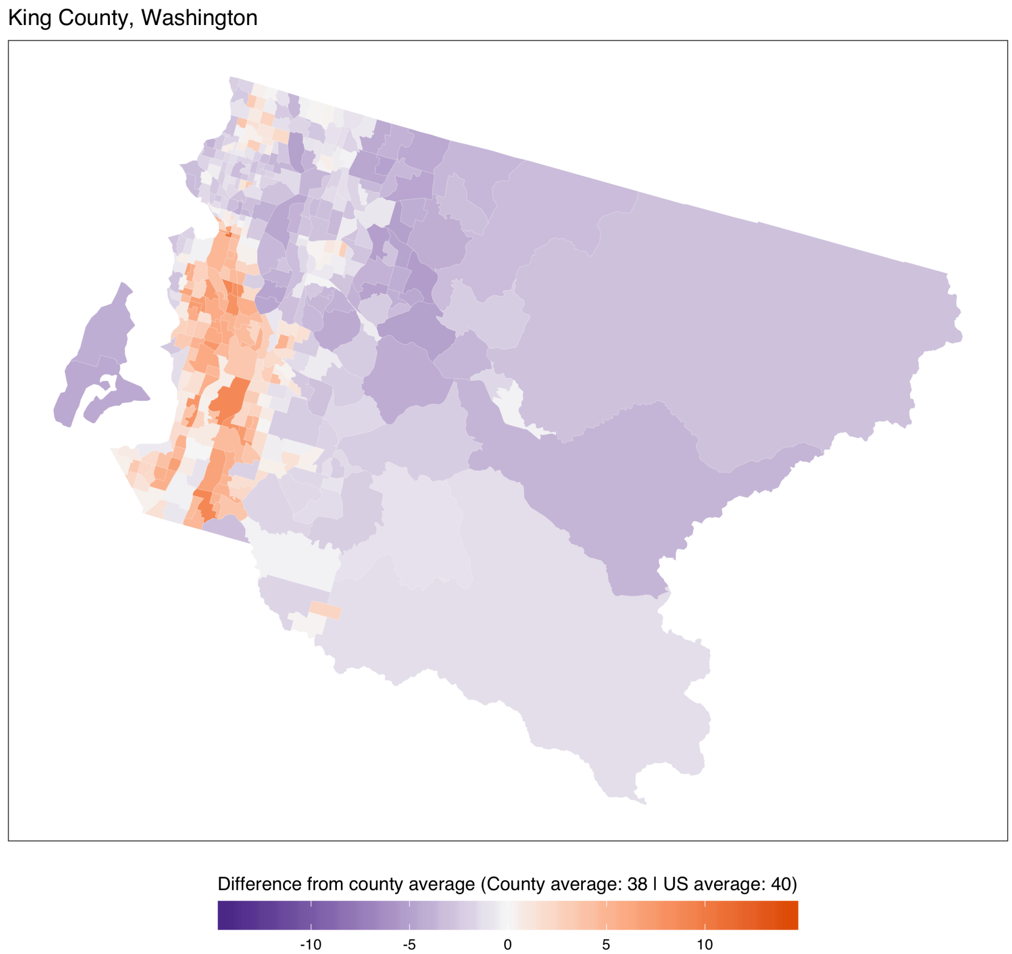

Fig. S15. Tract level estimates of heat risk perception for King County, WA. Tracts are shaded by the difference from the average for the county.

San Bernardino County, California

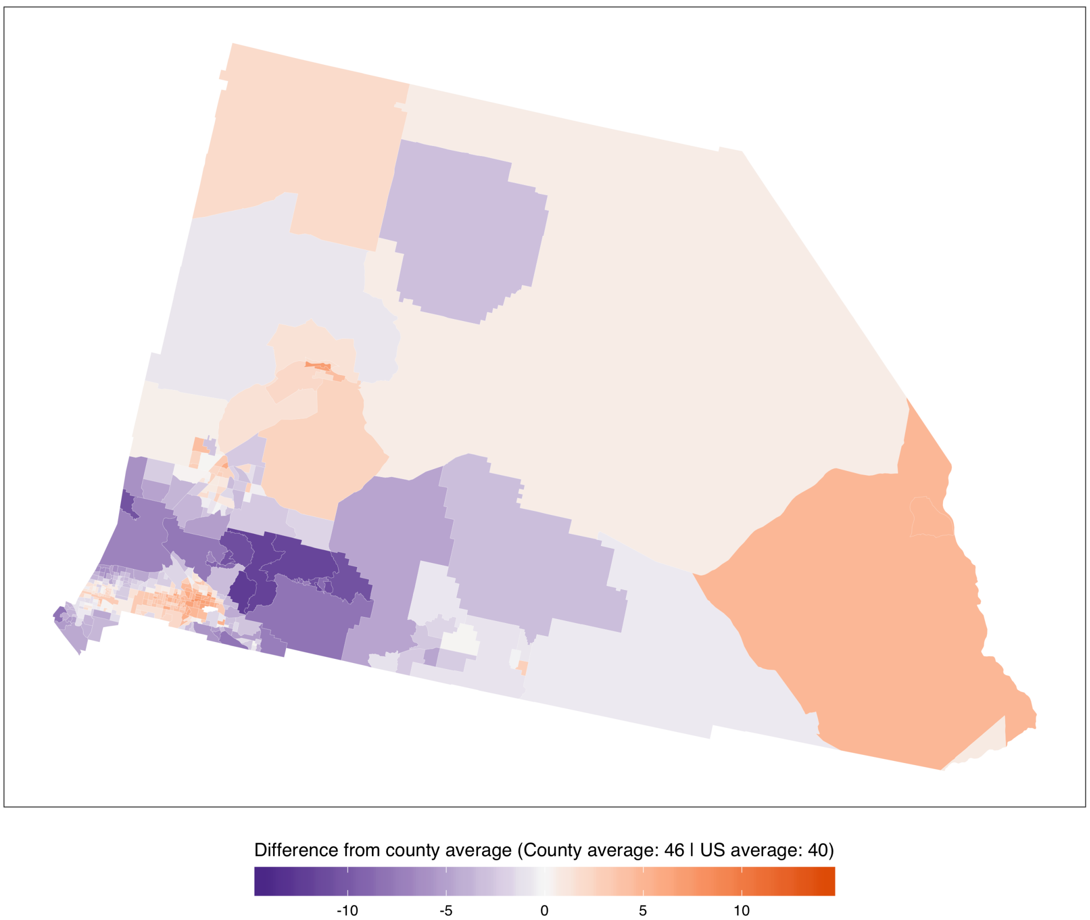

Fig. S16. Tract level estimates of heat risk perception for San Bernardino County, CA. Tracts are shaded by the difference from the average for the county.

Tarrant County, Texas

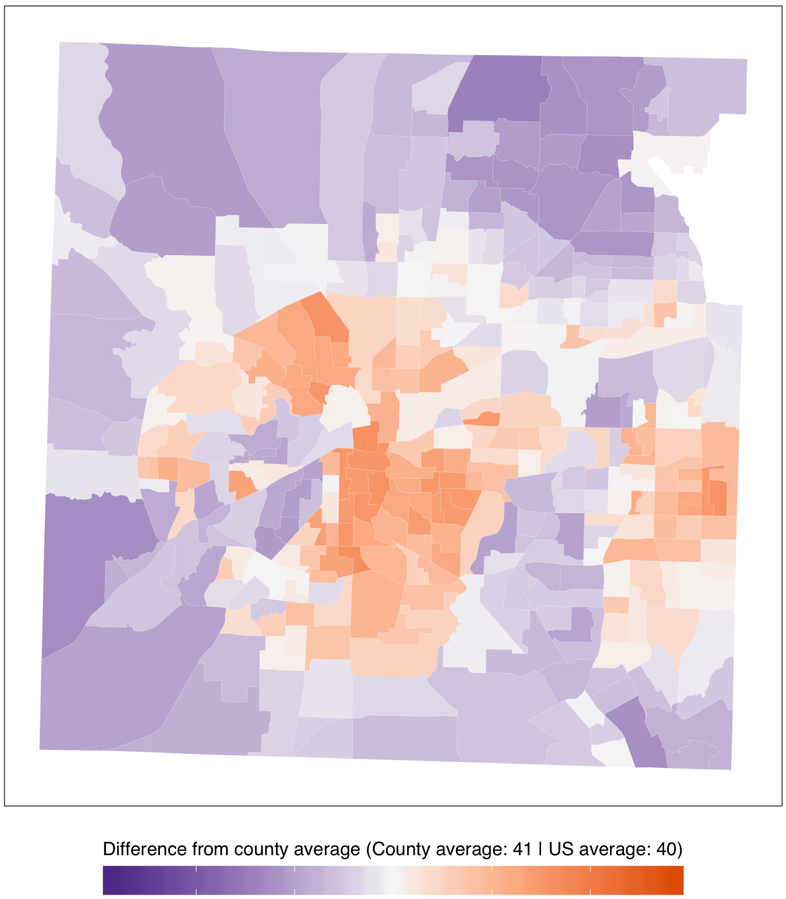

Fig. S17. Tract level estimates of heat risk perception for Tarrant County, TX. Tracts are shaded by the difference from the average for the county.

Bexar County, Texas

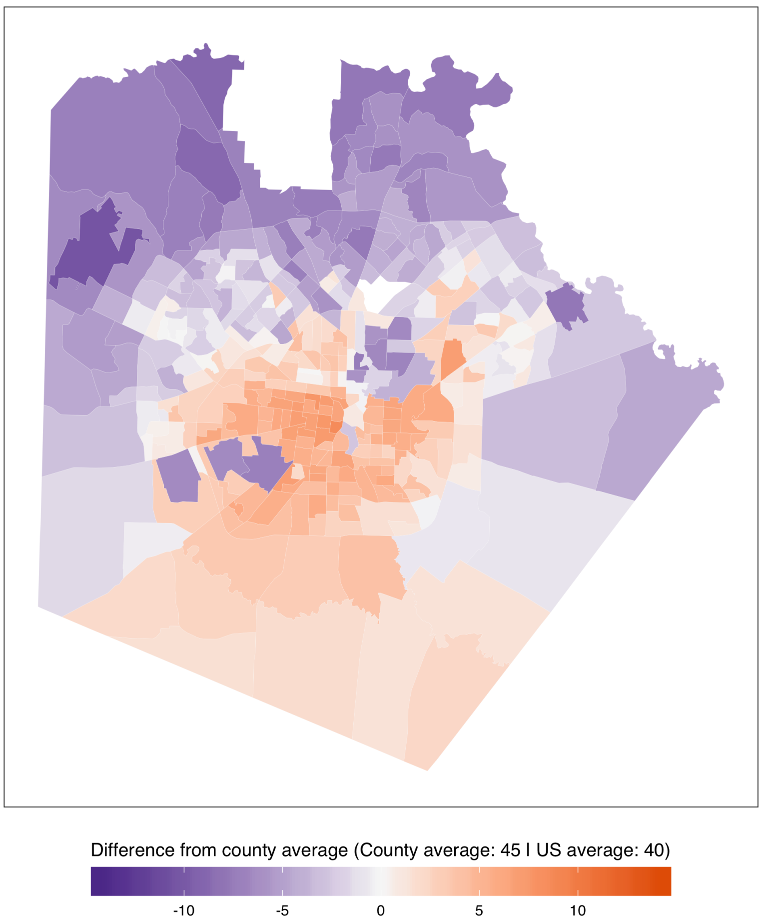

Fig. S18. Tract level estimates of heat risk perception for Bexar County, TX. Tracts are shaded by the difference from the average for the county.

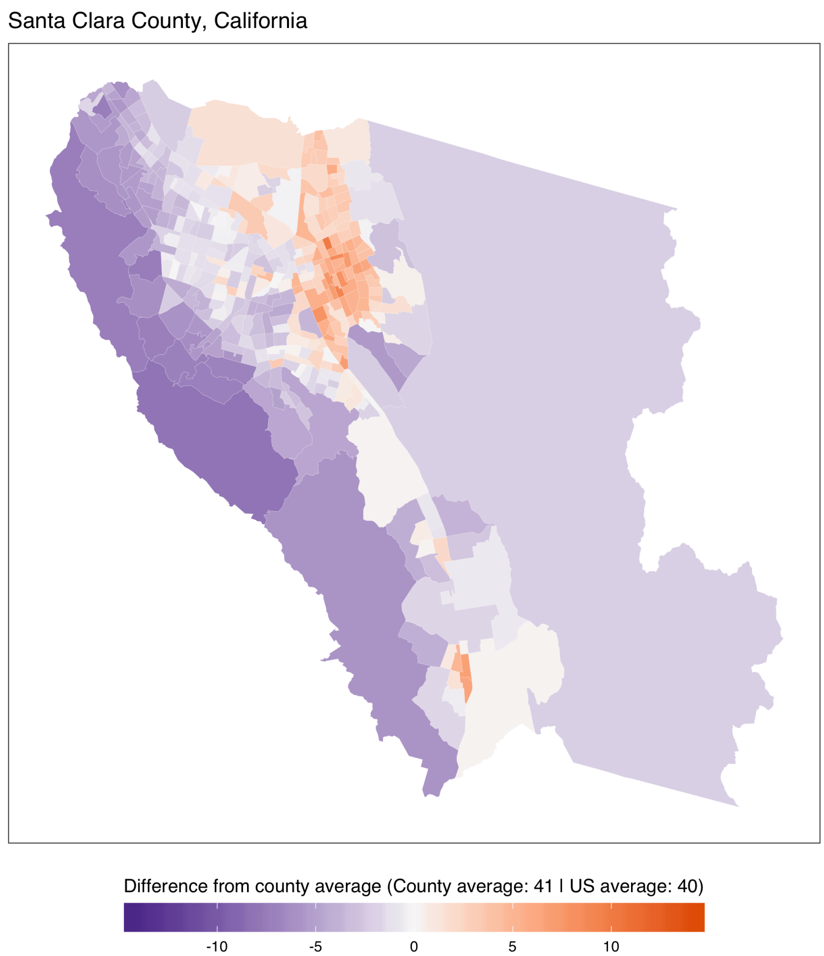

Fig. S19. Tract level estimates of heat risk perception for Santa Clara County, CA. Tracts are shaded by the difference from the average for the county.

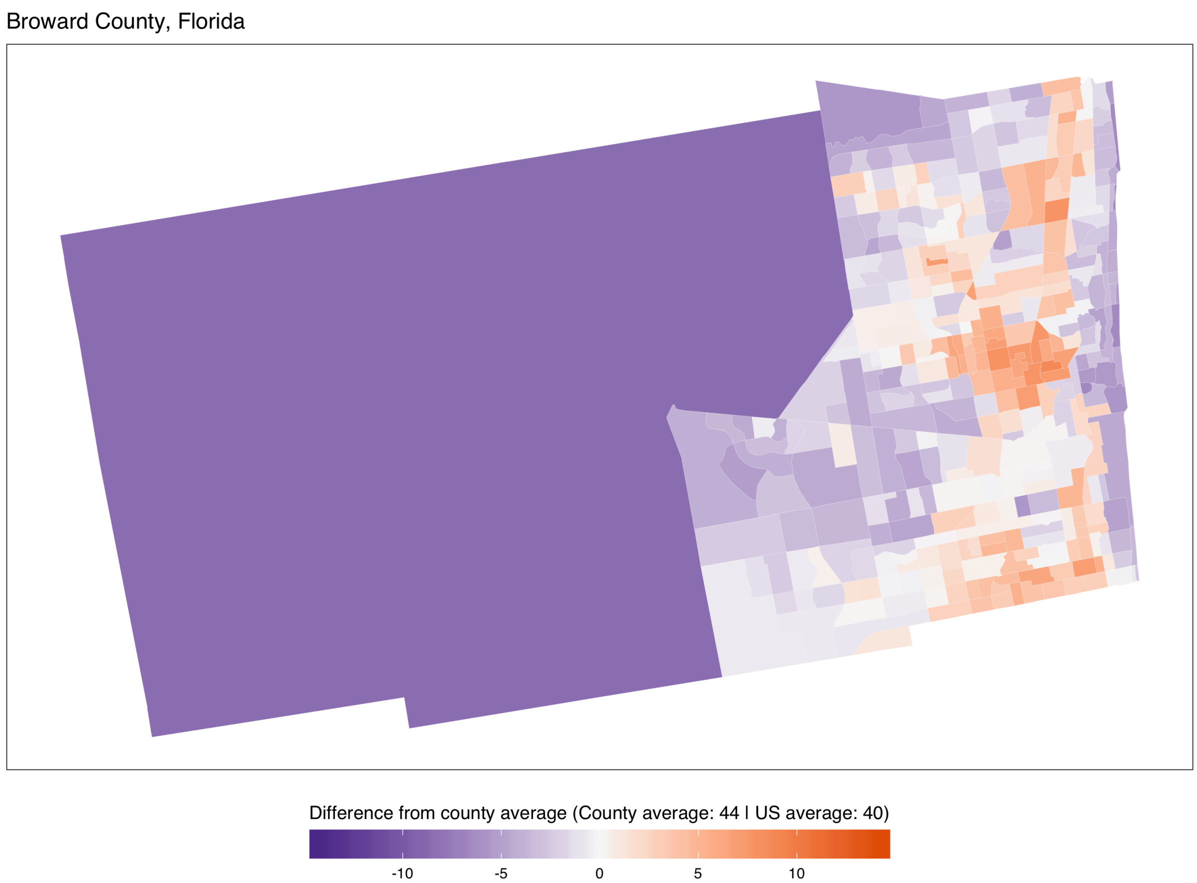

Fig. S20. Tract level estimates of heat risk perception for Broward County, FL. Tracts are shaded by the difference from the average for the county.

Wayne County, Michigan

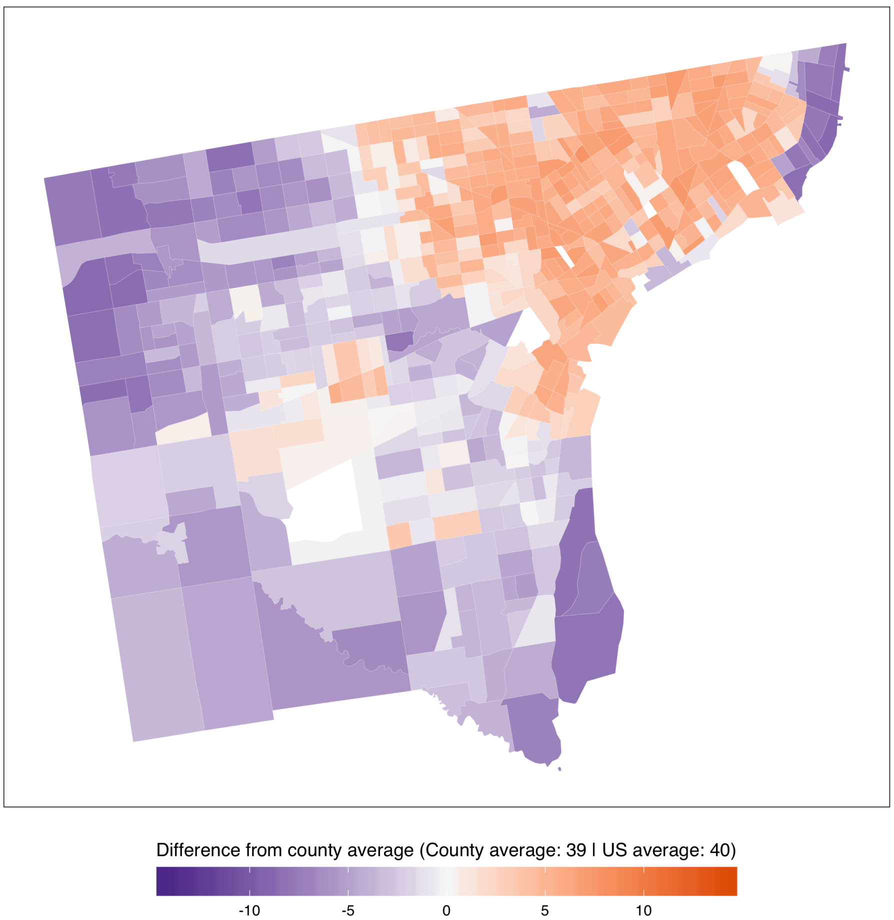

Fig. S21. Tract level estimates of heat risk perception for Wayne County, MI. Tracts are shaded by the difference from the average for the county.

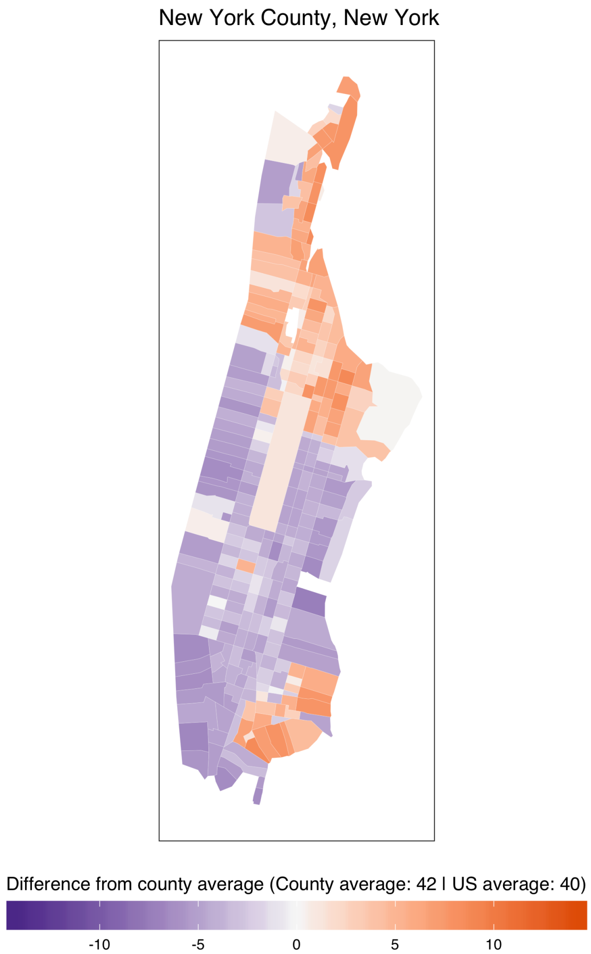

Fig. S22. Tract level estimates of heat risk perception for New York County, NY. Tracts are shaded by the difference from the average for the county.

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