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Housing and Urban Heat: Assessing Risk Disparities

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ABSTRACT

Heat is the leading weather-related cause of death in the United States, and housing characteristics affect heat-related mortality. This paper answers two questions. First, how do heat risk measures vary by housing type and location in San José, California? Second, what housing and neighborhood factors are associated with greater heat risk? We first create a parcel dataset with housing, heat risk, and neighborhood characteristics. We then use a combination of descriptive statistics, exploratory mapping, and linear regression models to analyze associations between housing, neighborhoods, and heat risk. The results indicate that households of different housing types face varying degrees of heat risk, and the largest disparities are between detached single-family (lowest heat risk) and multifamily rental (highest heat risk). Air conditioning availability is a major contributing factor: the probability of not having central air conditioning is much lower for detached single-family (44.9%) compared with multifamily rental (73.7%). There are also heat risk disparities for households in neighborhoods with larger proportions of Hispanic and Asian residents. This research demonstrates the need to understand heat risk at the parcel scale and suggests to policymakers the importance of heat mitigation strategies that focus on multifamily rental housing and communities of color.

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Climate adaptation; extreme heat; low-income housing; urban environment; California

Heat is the leading cause of weather-related death in the United States, and extreme heat events will continue to worsen with climate change (National Weather Service, 2018; U.S. EPA & CDC, 2016). Housing characteristics affect heat exposure and scholars are increasingly quantifying why and how (O'Neill et al., 2005; Samuelson et al., 2020; Taylor et al., 2015). For example, research has demonstrated that affordable housing and manufactured housing disproportionately lie at the intersection of heat and social disadvantage (Gabbe & Pierce, 2020).

There are several reasons why residents of lower-cost housing types—whether subsidized or unsubsidized—may be particularly exposed to extreme heat. People with lower incomes are more likely to live in neighborhoods with fewer trees and more pavement, to lack access to central air conditioning (AC) and financial resources for energy bills, and/or to work outside during the day (Gronlund, 2014; Harlan et al., 2006; Hayden et al., 2011; Jenerette et al., 2016; Mitchell & Chakraborty, 2015; Pearsall, 2017). Additionally, some housing structure types, particularly one-story detached housing, can increase interior thermal exposure beyond urban heat island (UHI)-related warming in an arid climate (Stone, Mallen, Rajput, Broadbent, et al., 2021).

Subsidized affordable housing is particularly important to study. The affordable housing stock provides a durable indicator of where low-income households will live in the future, and

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policymakers have the most leverage to influence the characteristics of affordable housing. As such, housing policymakers are increasingly interested in housing and climate adaptation. At the federal level, the 2014 U.S. Department of Housing and Urban Development (HUD) climate adaptation plan identified a lack of AC in public housing as a contributor to heat vulnerability, along with the potential for increased energy costs as a result of climate change (U.S. Department of Housing & Urban Development, 2014). The Green New Deal for Public Housing Act, a bill in Congress, would fund climate adaptation for HUD's public housing stock (Sanders & Ocasio-Cortez, 2021). At the state level, California's Affordable Housing and Sustainable Communities (AHSC) program includes extreme heat in its "climate resiliency" selection criteria (California Strategic Growth Council, 2021).

Our research analyzes intracity disparities in thermal exposure and adaptive capacity for different housing types. We answer two questions for San José, California, the tenth most populous city in the United States and the central city of Silicon Valley. First, how do heat risk measures (e.g., tree canopy, land surface temperature (LST), and central AC) vary by housing type and location? Second, what housing and neighborhood factors are associated with greater heat risk? We hypothesize that multifamily housing types, particularly those in which lower-income residents reside, are in hotter parts of the city and/or have characteristics that hinder heat adaptation.

We created and compiled several datasets to answer these questions. Housing characteristics at the parcel level were collected from county assessor records and City of San José affordable housing data. Tree canopy was calculated using the City of San José's tree inventory. LST data were from National Aeronautics and Space Administration (NASA)/United States Geological Survey (USGS) Landsat Collection 2 Analysis Ready Data. We modeled central AC prevalence at the parcel level using American Housing Survey (AHS) data by adapting an approach from Gronlund and Berrocal (2020). We also incorporated additional tract-level variables, including demographic and socioeconomic characteristics, from the U.S. Census American Community Survey.

Our approach combined descriptive statistics and linear regression models. We compared four measures—tree canopy, LST, central AC prevalence, and a heat risk index (HRI)—by housing type. We then specified regression models, at the parcel scale, to associate heat risk factors with key housing and neighborhood characteristics. The dependent variables were the four measures of heat risk mentioned above, and the independent variables included parcel and neighborhood characteristics.

This paper contributes to urban planning and environmental policy scholarship and practice by analyzing heat risk factors at a fine spatial scale and connecting these characteristics to housing by type, tenure, and affordability. Although several studies have used social vulnerability indices, or individual measures, to map neighborhood-level vulnerability, there has been limited study focused specifically on housing (Conlon et al., 2020; Reid et al., 2009; Wilson & Chakraborty, 2019). Additionally, although our three main heat risk measures are not novel in themselves, our combined analysis of outdoor and indoor heat risk measures at the parcel scale offers new insights into policies designed to mitigate heat exposure.

Literature Review

Climate change is likely to increase human exposure to extreme heat and worsen associated health effects—and these impacts will not be equally distributed. Socially vulnerable populations, namely those with lower incomes and people of color, face elevated risks of heat-related morbidity and mortality (Harlan et al., 2006). Vulnerability to heat is a function of an individual's heat exposure, sensitivity to heat, and adaptive capacity (Wilhelmi & Hayden, 2010). Heat risk factors affect the likelihood of negative health outcomes for an individual (Yardley et al., 2011).

Residents of urban areas are more exposed to heat due to the UHI effect (Founda & Santamouris, 2017; Heaviside et al., 2016; Li et al., 2015; Ruuhela et al., 2020; U.S. EPA, 2006; U.S. EPA & CDC, 2016). The increase in heat exposure due to the UHI, and particularly the role UHI plays in retaining higher nighttime temperatures, has been associated with an increased risk of heat-related illness and heat-related mortality for residents of urban areas (Heaviside et al., 2016; Laaidi et al., 2012; Li et al., 2015; U.S. EPA, 2006). For example, modeling attributed about 52% of heat-related deaths to the UHI during a 2003 heat wave in the West Midlands, UK (Heaviside et al., 2016). Relatedly, during an extreme heat event in Paris, the UHI was associated with increased risk of heat-related mortality by causing elevated nighttime temperatures and exposing urban residents to these elevated temperatures for a longer duration throughout the day (Laaidi et al., 2012).

Heat Risk by Race and Income

People of color face greater exposure to heat because of racist policies, including redlining and exclusionary zoning, that have historically segregated minority populations, placed them at economic disadvantage, and forced them toward lower quality housing. Broadly, institutional racism has left communities of color in segregated portions of the city that continue to experience hotter temperatures to this day (Chow et al., 2012; Jesdale et al., 2013; Mitchell & Chakraborty, 2014; Rosenthal et al., 2014; Wilson, 2020). The association between communities of color and urban heat has been attributed to the persistent effects of historical racist policies in the United States, of which "redlining" has been most studied (Hoffman et al., 2020; Wilson, 2020).

There are several ways that these racist policies manifest in today's built environment. In general, people of color are more likely to live in denser neighborhoods with less vegetative cover and more impervious surfaces (Gronlund, 2014; Harlan et al., 2006; Hoffman et al., 2020). Lastly, communities of color generally have access to fewer, smaller, and lower quality parks than communities that are predominantly white (Rigolon, 2016; Wolch et al., 2005).

Income is another predictor of urban heat exposure and adaptive capacity. Low-income neighborhoods have more vacant lots and less vegetative cover, both of which contribute to increased biophysical risk and exposure to heat (Harlan et al., 2006; Jenerette et al., 2016; Mitchell & Chakraborty, 2015; Pearsall, 2017; Voelkel et al., 2018). Low-income communities may also experience reduced adaptive capacity to heat (Byrne et al., 2016; Harlan et al., 2006; Hayden et al., 2011; Mitchell & Chakraborty, 2015; Uejio et al., 2011; Voelkel et al., 2018). Klinenberg's (2002) research studying the Chicago, Illinois, heat wave of 1995 found social isolation to be a factor in heat-related mortality. In general, aspects of social isolation have been correlated with increased heat health risk (Hayden et al., 2011; Uejio et al., 2011).

The Role of Housing in Reducing Heat Risk

A variety of building characteristics can mediate residents' heat exposure indoors (Ellena et al., 2020). Insulation and weatherization can play a role in moderating indoor temperature extremes; in general, homes with less insulation are more affected by heat because, without insulation, outdoor temperatures have a more direct impact on a home's indoor temperature, potentially elevating indoor temperatures to unsafe levels (Baniassadi & Sailor, 2018; Mavrogianni et al., 2012; White-Newsome et al., 2012). Increased insulation can be a tool to help reduce heat risk—particularly if the retrofits include upgrades to roof and window insulation, and if the building is located in an area that experiences high outdoor temperatures—although under some circumstances insulation may increase indoor temperatures in the absence of good nighttime ventilation by trapping heat indoors (Baniassadi & Sailor, 2018; Gronlund & Berrocal, 2020; Kenny et al., 2019; Mavrogianni et al., 2012). Large-scale implementation of roofs with high albedo, sometimes

called cool roofs, has been modeled to reduce the UHI and associated heat mortality rates (Macintyre & Heaviside, 2019).

Housing structure type and age affect indoor temperatures. Housing structure type had a major impact on modeled interior temperatures across a diversity of climates (Stone, Mallen, Rajput, Broadbent, et al., 2021; Stone, Mallen, Rajput, Gronlund, et al., 2021). For example, in Phoenix, Arizona: one-story, single-family structures without consistent AC access became even warmer than ambient temperatures during a heat wave, and were almost 40 °F higher than similar structures with working AC (Stone, Mallen, Rajput, Broadbent, et al., 2021; Stone, Mallen, Rajput, Gronlund, et al., 2021). Additionally, relationships between building age and heat have been well documented, with older homes experiencing higher indoor temperatures compared to their newer counterparts (Baniassadi & Sailor, 2018; Kenny et al., 2019; Nahlik et al., 2017; White-Newsome et al., 2012).

AC can play a particularly important role in reducing the risk of heat-related illness and heat-related mortality (O'Neill et al., 2005; Ostro et al., 2010; Rogot et al., 1992). Within the literature surrounding AC and heat risk, a distinction is made between central AC and room AC (also referred to as window AC), with the former being more effective in cooling indoor temperatures to healthy, comfortable levels (Ostro et al., 2010; Quinn et al., 2017; Rogot et al., 1992). The provision of central AC is often mediated by the age of the housing stock, with newer buildings being more likely to have central AC (Fraser et al., 2017; Gronlund & Berrocal, 2020). Further, several studies have connected race, ethnicity, and income to AC availability, identifying a lower prevalence of central AC among low-income households and households of color (Harlan et al., 2013; Madrigano et al., 2018; O'Neill et al., 2005).

Low-income households often lack the ability to afford household-scale adaptation and mitigation measures, making them more susceptible to the harms of heat (Hayden et al., 2011; Voelkel et al., 2018). For example, energy costs may inhibit low-income households from running air conditioners regularly or to the degree necessary for thermal comfort (Hayden et al., 2011; Walker, 2015). Additionally, low-income households may be less able to pay for AC maintenance and repairs, or are reliant on landlords, depending on the circumstances (Wright et al., 2020). Low-income households thus may be more dependent on public places for cooling than wealthier residents (Berisha et al., 2017; Fraser et al., 2017).

What We Need to Know About Housing and Heat Risk

There is limited evidence about how these disparities are related to housing types. We do know that affordable housing and manufactured housing are disproportionately at the intersection of heat and social disadvantage in California (Gabbe & Pierce, 2020), and there were higher temperatures around affordable housing relative to market-rate housing in Portland, Oregon (Voelkel et al., 2018). Vulnerable populations may be exposed to high indoor temperatures, including seniors in public housing and farmworkers (Quandt et al., 2013; Tsoulou et al., 2020).

Focusing on residential heat risk is important because people in the United States spend more hours every day at home than any other place, and even more so during the COVID-19 pandemic (U.S. Bureau of Labor Statistics, 2020). People over the age of 65, the age group most at risk of heat-related morbidity and mortality, spend more time at home than any other age group (Balbus & Malina, 2009; Meade et al., 2020; U.S. Bureau of Labor Statistics, 2020). Even beyond the pandemic, the shift toward telework culture may result in even more time spent at home during peak hours of the day, exposing people to their home temperatures during working and nonworking hours. Those living without AC at home, in a warmer area of their city, or in a warmer housing type will be at greater risk of high heat exposure than those who have traditionally worked in air-conditioned office settings. Differentiating by housing type is essential because interventions to mitigate heat risk may be different for, say, the owner of a single-family dwelling than for the owner of a multifamily development occupied by renters.

Data and Methods

We focused our analysis on San José for several reasons. San José is a large American city (population of about one million, 10th largest in the United States) and has one of the country's most expensive housing markets, with average home values of over $1.4 million (U.S. Census Bureau, 2019; Zillow, 2022). There are also considerable economic disparities in the city, ranging from the 7% of the population that is in poverty to high-tech multimillionaires and billionaires (U.S. Census Bureau, 2019). San Jose is in International Energy Conservation Code (IECC) climate zone 3, which includes most California cities, along with some cities in Texas and across the southern United States, and is defined as having a Mediterranean climate with warm and dry summers in the Köppen-Geiger climate classification (Peel et al., 2007; U.S Department of Energy, 2015).

Below, we describe the sources of our data on housing and neighborhood characteristics, tree canopy, LST, and AC provision. We also describe the methods used to analyze relationships between housing types and urban heat risk in San José.

Data on Housing and Neighborhood Characteristics

The primary source of housing data was the Santa Clara County Assessor, with 2018 parcel locations and land use codes. We used these data to select residential parcels with the use code of single-family, two-family, three- or four-family, five-family or more, and townhouse/condo.[1] We recoded these data into three categories: detached, attached owner, and attached rental.

The assessor's data does not indicate whether the housing on a parcel is subsidized/affordable, so we incorporated data from the city of San José to address this. We obtained the city of San José's 2020 inventory of affordable housing developments, which included locations and unit counts (City of San José, 2020). We spatially joined each affordable housing development with its associated parcel from the assessor's dataset. Based on this join, we added a fourth category of housing type to the three mentioned in the previous paragraph: "attached rental (affordable)." We refer to the other attached rental units as "attached rental (market-rate)" throughout this paper. We added two other housing characteristics based on the assessor's data: year of construction and number of housing units on the parcel.

Neighborhood built environment, socioeconomic, and demographic characteristics were obtained from the U.S. Census. We used tract-level data from 2019 American Community Survey 5-year estimates (U.S. Census Bureau, 2019). The variables that we obtained or calculated from Census estimates were population per square mile; age (proportion of residents under the age of 5; and proportion of residents over the age of 65); median household income; race and ethnicity (proportions of Black population; Hispanic population; Asian population); housing tenure; and proportion of the population with at least a bachelor's degree.

Tree Canopy and Temperature Data

We calculated tree canopy coverage from high-resolution City of San José land cover data. A 2012 tree canopy inventory was conducted by University of California, Davis researchers for the city government and was provided as a shapefile (City of San José, 2012). We converted the data to a raster with a resolution of 3 m and used Geographic Information Systems (GIS) zonal statistics tools (QGIS 3.8) to estimate the mean tree canopy coverage of each parcel.

We calculated LST in degrees Fahrenheit using satellite data for August 9, 2020, from Landsat 8 Collection 2 Analysis Ready Data (USGS, 2021). This date was chosen to represent a typical hot—though not extreme—day in San José, with a high temperature of 88 °F (NOAA, 2020). By comparison, the historical average high temperature in the summer months in San José (1981–2010) was 82.2 °F (NOAA, 2020). Additionally, the chosen date had clear skies, which was particularly important given the presence of wildfire smoke for much of the hottest part of the

summer season of 2020. The mean LST for each parcel was calculated using the same approach as for the tree canopy data described above. Although LST is not a direct proxy for air temperature, it can be used to represent relative spatial prioritization, highlighting areas in greater need of cooling interventions as compared to others within the same city.[2]

AC Data and Model

Our conceptual model is that the likelihood of a household having AC is a function of unit and household characteristics. Detailed data on AC provision are seldom available—and this was the case in Santa Clara County—so we modeled AC provision at the parcel level using a combination of AHS metropolitan data, county assessor parcel data, and local affordable housing data. To do this, we adapted the approach of Gronlund and Berrocal (2020).

The AHS is a representative national sample of housing units and a sample of metropolitan areas on a rolling basis, including data on AC provision. The AHS included a metropolitan sample for the San José–Sunnyvale–Santa Clara Metropolitan Statistical Area (MSA) in 2017. We recoded the primary AC question from the AHS ("Type of primary air conditioning") into three categories: (1) central AC, (2) window AC, (3) and no AC.

We first summarized AC provision at the metropolitan level with a set of key housing characteristics. We used the AHS survey weights provided by the Census Bureau and the 'survey' package in R to summarize overall AC availability and by housing tenure, type, subsidy, and year built (Lumley, 2020; United States Census Bureau, 2017).

Next we used a logistic regression model to regress AC availability on housing characteristics for metropolitan San José. We separately modeled two binary outcomes: any AC, which includes both central and window AC, and central AC only. We created a parsimonious model that only includes variables readily available in both the AHS and Santa Clara County (SCC) assessor data: multifamily housing (indicator); affordable housing (indicator, joined with SCC assessor data from the city of San José); and year built. The logistic regression models take the form of Equation (1):

$$AC = f(\textit{housing type}, \textit{year of construction}, \textit{presence of subsidy}) \quad (1)$$

We then developed a predictive model of AC provision that could be applied to parcels in San José. We used the 'caret' package in R to develop a predictive model of AC provision based on the 2017 AHS data for metropolitan San José (Kuhn, 2020). We partitioned the data into training (80%) and testing (20%) datasets to develop our predictive models. We tested five types of predictive models appropriate for binary outcome variables: k-nearest neighbors, logit, LogitBoost, Logistic Model Trees, and Naive Bayes. We compared the results from the models and selected the logit model, which had the best balance of accuracy, sensitivity, and specificity. Applying the logit model of "Central AC" provision to the testing dataset provided an accuracy of 0.61, model sensitivity of 0.56, and specificity of 0.63.

We used these models to estimate the probability of central AC availability by parcel and census tract.[3] As a check, the mean parcel estimate of central AC was 52.7%; by comparison the San José metropolitan average based on the AHS data for central AC was 51.1%.

Heat Risk Index

The HRI is a simple combined measure of a residential parcel's heat risk. The two exposure components of the HRI are the proportion of each parcel not covered by tree canopy, and the mean LST for each parcel. The adaptive capacity component of the HRI is the probability of the parcel not having central AC. Exposure and adaptive capacity are equally weighted in the HRI, and thus

the overall weights are the proportion of the parcel without tree canopy (25%), LST (25%), and probability of no central AC (50%).

To calculate the HRI these three components were first standardized by creating *z* scores. We assigned a numerical value based on the number of variations from the mean value, following Wilson and Chakraborty (2019) and Reid (2009). The possible range for the HRI was between 2 and 12. The lowest value would be achieved if the parcel scored at least 2 standard deviations below the mean in terms of both exposure and adaptive capacity, and the highest value would be achieved if the parcel was more than two standard deviations above the mean on both components.

Regression Models

Our regression approach allows us to identify associations between housing characteristics and heat risk outcome variables. Our unit of analysis was the parcel, and we broadly regressed parcels' heat-related characteristics on sets of housing (parcel) and neighborhood (tract) variables.

We created four sets of regression models, with each set having one of the following outcome variables as a measure of heat risk: (1) proportion of the parcel without tree canopy; (2) LST on August 9, 2020; (3) probability of not having central AC; and (4) the HRI. Again, each of these outcomes was scaled such that lower values imply lower heat risk.

The independent variables included housing and neighborhood characteristics. Our primary independent variable of interest was the categorical variable for housing type. The other housing variables are year of construction and number of housing units on the parcel. Other independent variables, all at the tract scale, pertained to the built environment (i.e., population density), residents' age (i.e., population proportion below 5 years, proportion above 65 years), race and ethnicity (i.e., proportion Black, proportion Asian, proportion Hispanic), and economic characteristics (i.e., proportion renters, median household income).

We specified ordinary least squares (OLS) models in the form of Equation (2). We included spatial fixed effects—ZIP codes—to control for unobservable neighborhood factors, following an established econometric approach in parcel-scale models (Kuminoff et al., 2010).[4] We also clustered the standard errors by census tract to account for the nonindependence of nearby observations. We calculated the variance inflation factor values for our independent variables, all of which were under 4.0, giving us little reason for concern about multicollinearity.

$$\textit{Heat risk factor} = f(\textit{housing type}, \textit{housing characteristics}, \textit{neighborhood sociodemographic characteristics}) \quad (2)$$

Results

We begin with descriptive statistics generally (Table 1) and by housing type and heat risk factor (Table 2 and Figure 1), and then show statistical associations between housing and heat risk, all else being equal, from the regression analysis (Table 3).

Housing Characteristics and AC Availability in Metropolitan San José

AHS data for metropolitan San José, which includes all of Santa Clara County, illustrate patterns of AC availability by housing type and characteristics (Figure 2). In metropolitan San José, owners were more likely to have any type of AC (72.1% vs. 67.5%), and especially central AC (60.5% vs. 40.0%), relative to renters. Single-family housing, large multifamily, and manufactured

Table 1. Descriptive statistics ($N = 212{,}336$).

Indicator	Mean	SD	Min	Pctl(25)	Median	Pctl(75)	Max
Housing units on parcel	1.47	9.75	1	1	1	1	1,750
Year of construction	1970	21	1864	1960	1970	1981	2021
No tree canopy (parcel proportion)	0.83	0.08	0	0.8	0.8	0.9	1
LST on August 9, 2020	111.44	2.98	82.36	109.73	111.8	113.57	120.14
LST on September 29, 2021	92.79	2.81	73.78	91.07	93.05	94.85	102.53
No central AC	0.47	0.15	0.14	0.39	0.47	0.56	0.94
Heat risk index	6.89	1.21	2	6.00	7.00	7.50	11.00
Pop. per sq. mi	9,017	4,492	2	6,674	8,298	11,108	60,386
Pop. under 5 years (proportion)	0.05	0.02	0.01	0.03	0.04	0.05	0.09
Pop. over 65 years (proportion)	0.12	0.05	0	0	0	0	0
Median household income	127,059	43,100	26,019	98,378	121,543	152,045	250,001
Renter households (proportion)	0.34	0.2	0.03	0.17	0.29	0.46	1
Black pop. (proportion)	0.03	0.02	0	0.01	0.02	0.03	0.19
Hispanic pop. (proportion)	0.27	0.19	0.01	0.13	0.22	0.36	0.78
Asian pop. (proportion)	0.36	0.21	0.03	0.2	0.28	0.52	0.82

AC = air conditioning. LST = land surface temperature. SD = standard deviation.

Table 2. City of San José parcel mean values and mean *z* scores by housing type.

	% parcel without tree canopy		Land surface temp. (°F) on August 9, 2020		Prob. of no central AC		Heat risk index
	Mean value (%)	Mean *z* score	Mean value	Mean *z* score	Mean value (%)	Mean *z* score	Mean value
Detached	83.1	0.03	111.6	0.07	44.9	−0.16	6.8
Attached owner	81.5	−0.18	110.1	−0.44	52.4	0.33	7.1
Attached rental (market rate)	82.5	−0.05	112.1	0.22	73.7	1.70	8.6
Attached rental (affordable)	84.0	0.14	111.4	−0.01	50.5	0.21	7.4

AC = air conditioning.

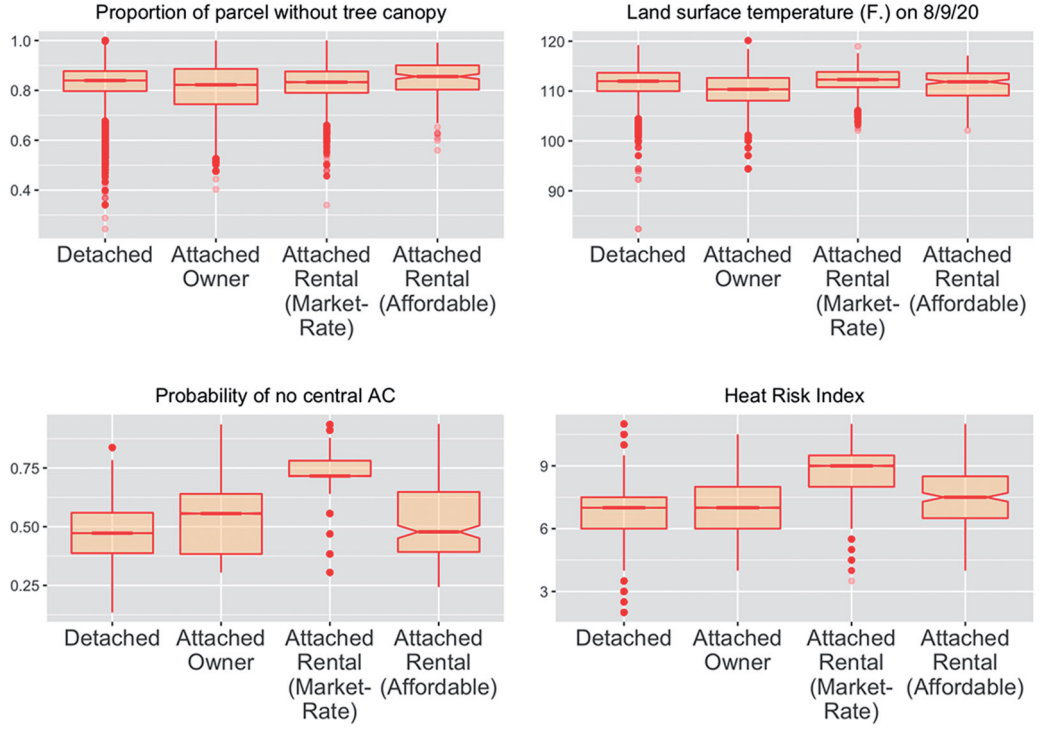


Figure 1. Comparison of heat risk factors by housing type (parcel-level).

Table 3. Regression of heat risk factors on parcel housing and neighborhood characteristics (ordinary least squares models).

	% parcel without tree canopy		Land surface temp. (°F) on August 9, 2020		Prob. of no central AC		Heat risk index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attached owner	−0.017*** (0.0005)	−0.039*** (0.006)	−1.505*** (0.018)	−1.095*** (0.220)	0.076*** (0.001)	0.224*** (0.002)	0.334*** (0.007)	1.208*** (0.065)
Attached rental (market rate)	−0.006*** (0.001)	0.004 (0.004)	0.457*** (0.030)	0.611*** (0.133)	0.291*** (0.001)	0.217*** (0.004)	1.910*** (0.012)	1.490*** (0.059)
Attached rental (affordable)	0.015** (0.005)	−0.007 (0.008)	−0.343 (0.197)	0.204 (0.236)	0.059*** (0.009)	0.219*** (0.004)	0.647*** (0.077)	1.581*** (0.082)
Housing units on parcel		−0.0001** (0.00004)		−0.003** (0.001)		0.00002 (0.00001)		−0.001* (0.0003)
Year of construction		0.001*** (0.0001)		−0.004 (0.004)		−0.007*** (0.0001)		−0.039*** (0.001)
Pop. per sq. mi (1,000 s)		−0.001 (0.001)		0.085** (0.029)		−0.0001 (0.0003)		0.004 (0.008)
Pop. under 5 years (proportion)		0.142 (0.184)		6.013 (6.707)		0.038 (0.060)		1.630 (1.912)
Pop. over 65 years (proportion)		−0.096 (0.077)		1.408 (3.102)		0.004 (0.026)		0.335 (0.815)
Median household income (1,000 s)		0.00004 (0.0002)		−0.010 (0.006)		0.00004 (0.00004)		−0.0005 (0.002)
Renter households (proportion)		−0.019 (0.026)		−2.903** (0.883)		−0.003 (0.008)		−0.519* (0.250)
Black pop. (proportion)		−0.012 (0.104)		3.506 (4.824)		−0.045 (0.033)		0.314 (1.275)
Hispanic pop. (proportion)		0.147*** (0.039)		7.746*** (1.530)		0.017 (0.013)		2.638*** (0.448)
Asian pop. (proportion)		0.131*** (0.030)		5.808*** (1.301)		−0.016 (0.010)		1.953*** (0.338)
Fixed effects	None	ZIP code	None	ZIP code	None	ZIP code	None	ZIP code
No. of observations	212,336	212,336	212,336	212,336	212,336	212,336	212,336	212,336
R^2	0.006	0.294	0.034	0.503	0.174	0.962	0.113	0.645
Adjusted R^2	0.006	0.294	0.034	0.502	0.174	0.962	0.113	0.645
Residual standard error	0.077 ($df = 212,332$)	0.065 ($df = 212,286$)	2.930 ($df = 212,332$)	2.102 ($df = 212,286$)	0.141 ($df = 212,332$)	0.030 ($df = 212,286$)	1.143 ($df = 212,332$)	0.723 ($df = 212,286$)
F Statistic ($df = 3$; 212,332)	430.484***		2,466.607***		14,871.580***		8,995.665***	

Note. AC = air conditioning. The reference group for the categorical housing variable is detached single-family.
*$p < .05$. **$p < .01$. ***$p < .001$.

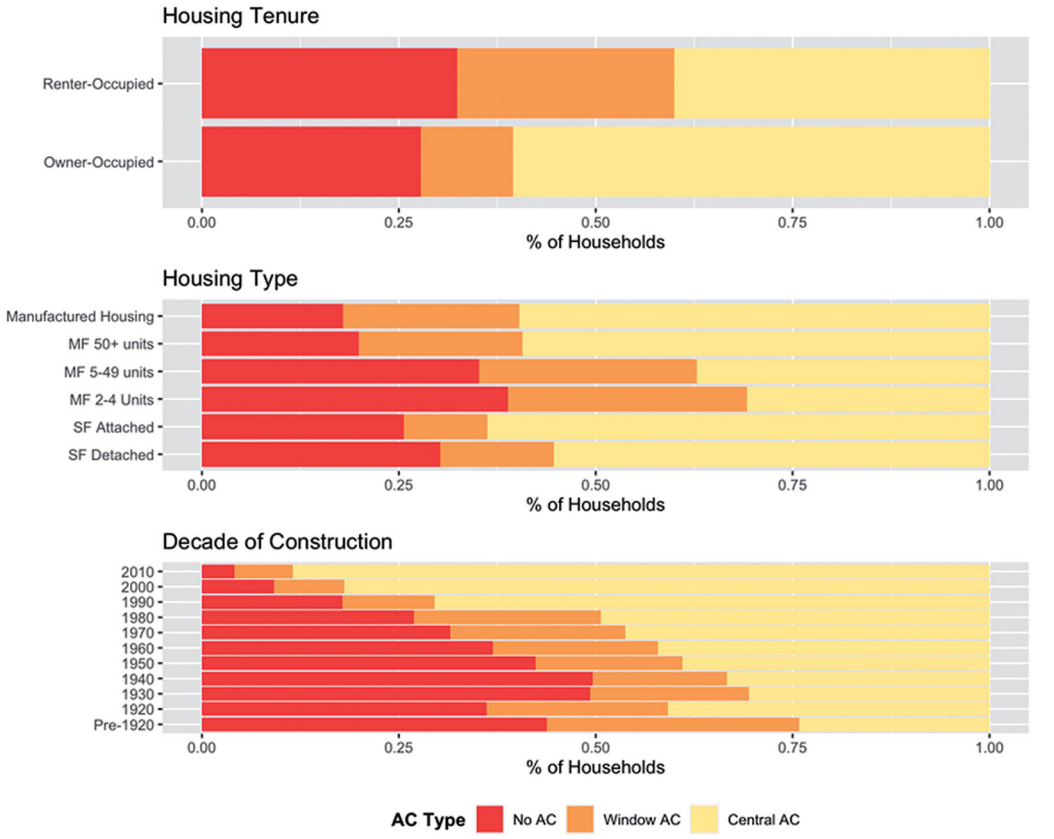


Figure 2. Air conditioning availability by housing characteristics for metropolitan San José (U.S. Census Bureau, 2017).

housing units were more likely to have central AC, or any AC, compared with smaller multifamily housing types. Housing age was connected to having AC access; for example, whereas 88% of units built in the 2010s had central AC, only 49% of units built in the 1980s had central AC, and availability was generally lower for each preceding decade (with the exception of units built in the 1920s).

Housing, Location, and Heat Risk

Tree canopy—or lack thereof—was distributed relatively evenly across various housing types in San José. All of the housing types were on parcels, on average, where 81.5–84.0% of the land area lacked tree canopy. Affordable housing had the least tree canopy, with 84% of the parcel area lacking tree canopy cover. This was followed by detached (83.1%), attached market-rate (82.5%), and attached owner-occupied (81.5%) housing. The *z* scores show that the averages for all four housing types are relatively close to the overall mean.

The four housing types averaged somewhat comparable LSTs. The hottest housing type was attached market-rate (112.1 °F), followed by detached and affordable with average LSTs of 111.6 °F and 111.4 °F, respectively. Lastly, attached owner-occupied housing was on parcels with the lowest temperatures, averaging 110.1 °F. The *z* scores indicate the largest differences from the overall mean ranged from −0.44 (attached owners) to 0.22 (market-rate multifamily).

Of the three heat risk measures, there was the most variation in the probability of no central AC. Detached housing had the lowest probability of no central AC (44.9%), meaning that the

majority of detached housing units do have central AC. The probability of central AC for affordable and owner-occupied attached was roughly 50–50, with average probabilities of no AC of 50.5% and 52.4%, respectively.[5] Attached market-rate housing was least likely to have AC—by a considerable margin—with an average 73.7% probability of no central AC. The *z* score for attached market-rate housing indicates that this housing type was 1.7 standard deviations above the mean on average.

The HRI demonstrates disparities between the four housing types. Attached rental housing was associated with the highest heat risk (8.6), followed by affordable (7.4), attached owner-occupied (7.1), and detached (6.8) housing.

There was spatial variation in the four heat risk measures. San José had less tree canopy in its eastern and, to some extent, southern neighborhoods. The hottest neighborhoods in terms of LST tended to be in the city's eastern and central neighborhoods, including downtown. The older core neighborhoods of the city included most of San José's pre-World War II housing and, relatedly, its housing with the lowest probability of central AC. In terms of overall HRI scores, the areas of greatest concern include East San José, downtown, and more exurban parts at the southern edge of the city limits (Figure 3).

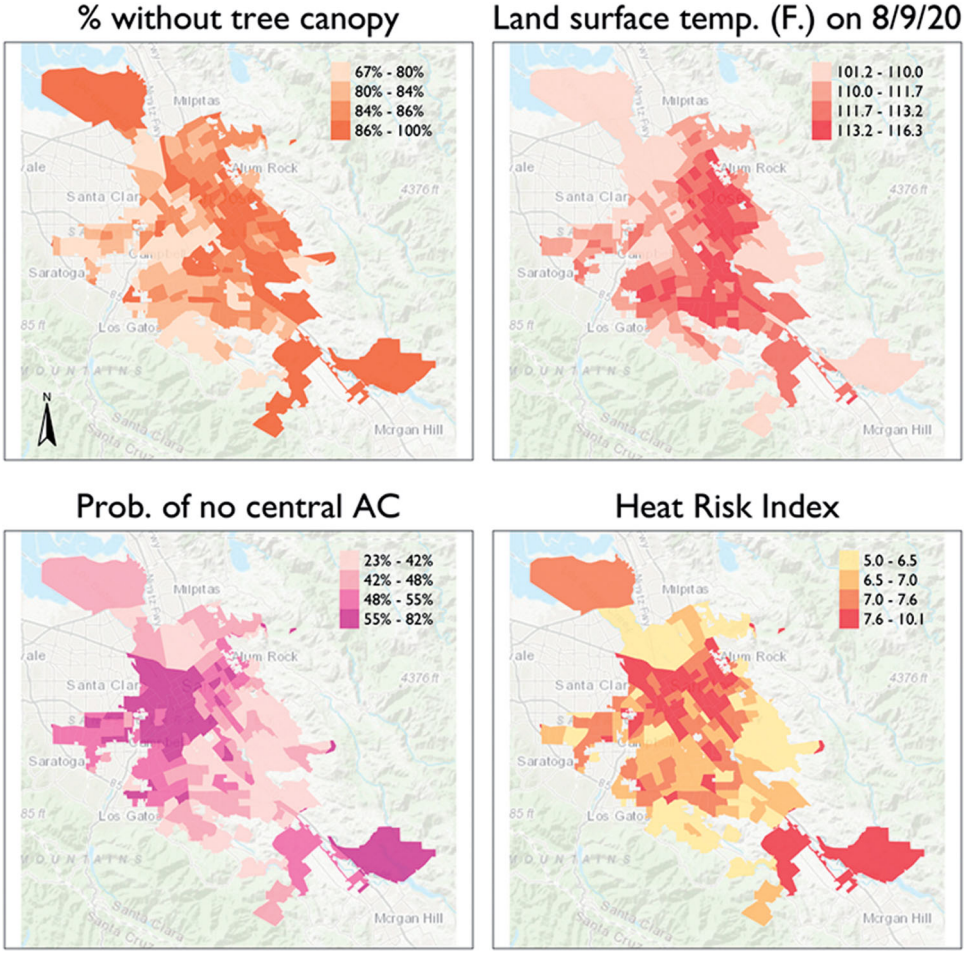


Figure 3. Comparison of heat risk factors by census tract (mean of residential parcels). AC = air conditioning.

Regression Results

We used regression models to explore relationships between the four heat risk measures described above and the housing and neighborhood characteristics of San José (Table 3 and Appendix Tables A1 and A2).

The three attached housing types generally faced greater heat risk than detached single-family housing did. Again, the reference group was single-family units, and this is the housing type relative to which comparisons are made. Market-rate multifamily had less tree canopy, was located in relatively hotter areas, and was less likely to have central AC. Attached owner housing was found in locations with more tree canopy and cooler temperatures, although it had a lower probability of having central AC. Affordable housing was significantly different from single-family in terms of having less central AC, and it fared worse on the overall HRI.[6]

The age of a housing unit was associated with some heat risk variables. Newer housing tended to be in areas with less tree canopy and was also more likely to have central AC. Generally, the heat risk associated with newer housing was lower than that for older housing.

There were also disparities by race and ethnicity, particularly for Asian and Hispanic residents. Parcels in neighborhoods with larger proportions of Asian and Hispanic residents had fewer trees and were hotter. There were no significant associations in terms of neighborhoods with larger proportions of Black residents. For the overall HRI, neighborhoods with more Asian and Hispanic residents faced greater heat risk; the proportion of Black residents was not significantly associated with the HRI outcome.

A limited number of other population characteristics were associated with heat risk. Neighborhood density was associated with higher temperatures. Neighborhoods with more renters were associated with lower LSTs and lower values on the HRI. Lastly, all else being equal, age and income[7] were not significantly associated with any of the heat risk factors.

Discussion

Our three main findings are that (1) tree canopy and temperature vary by housing type, but the biggest difference between housing types is in central AC availability; (2) households in rental multifamily generally face greater heat risk than those in single-family rental housing; and (3) affordable housing fares better than other rental multifamily. This has implications for policy, as described below.

The biggest disparity in heat risk by housing type is in terms of central AC, rather than tree canopy or temperature. This is important because past research has associated central AC access with health outcomes. Although central AC is widely available in newer and more expensive housing units, older and lower-cost attached housing units frequently lack central AC. The AHS metropolitan data for San José indicate that many residents of these units have portable or window AC units. We do not know, however, the coverage of these units, their efficiency, and/or the ability of households to afford to run AC (whether central or window). It seems reasonable to expect that the thermal comfort of residents with central AC will exceed that of those with window AC.

There have been several policy responses intended to make residential AC more accessible and affordable for low-income and senior households. New York City, for example, has a program to provide a portable AC unit to low-income residents with a documented medical condition (City of New York, 2021). More broadly, utility assistance programs—particularly the federally-funded and state-administered Low Income Home Energy Assistance Program (LIHEAP)—may also help low-income households to afford the cost of cooling their homes (Perl, 2014). In the absence of sufficient residential AC, local governments should offer expanded and appealing cooling center options near residents, and encourage developers to include air-conditioned common areas in multifamily housing.

The housing types of most concern as indicated by this study are attached housing types, and particularly housing for low-income renters. Although many attached market-rate rental and owner-occupied housing units are in the same general areas, we particularly focus on low-income residents because they may have higher sensitivity and lower adaptive capacity that would increase their risk of heat-related morbidity or mortality. When thinking about multifamily rental housing, we noted that there are many styles of multifamily housing, from small "mom-and-pop" buildings to large, new upscale developments with resort-style amenities. Thus, the nature of the intervention should address the specific issues with the development in question.

Income, especially at the household level, is an important consideration when targeting interventions for heat resilience. Although tract-level income and heat risk are negatively correlated in San José (illustrated in Appendix Figure A1), our regression analysis indicates that parcel housing types are more likely to be statistically associated with parcel heat risk than is a tract's median household income. Our categorical housing type variable to some extent captures parcel-scale variation in household income. Although we do not have household income data at the parcel level, 2019 American Community Survey data help to illustrate relationships between housing type, tenure, and household income in San José. For example, the median household income for an owner-occupied unit was about $142,000, and more than three quarters (76.6%) of homeowners lived in a detached unit (U.S. Census Bureau, 2019). Meanwhile, the median household income was $77,000 for a renter-occupied unit and most renters lived in attached housing (76.5%; U.S. Census Bureau, 2019).

Shade should be expanded through activities of local government, nonprofit organizations, developers, and property owners. Our analysis can best inform policies to create shade through equitably expanding San José's tree canopy, and we have also observed opportunities for human-created shade such as shade sails, awnings, or shade structures, in areas where tree planting may not be feasible or desirable. Tree planting, on private property and in the public realm, should continue to be part of the local approach to mitigating urban heat. Parks and open spaces should play an important role, and these spaces can provide co-benefits beyond heat mitigation. But human-created shade for housing, which would be primarily on private property, can be implemented quickly and should be encouraged in new building designs and in renovations of existing structures. Local governments should consider shade standards for new construction and there could be incentive programs at the local or state level.

The target audience for most, but not all, multifamily heat interventions will be the property owner rather than the resident. This includes Heating, ventilation, and air conditioning (HVAC) systems, which were a focus of our analysis, and energy efficiency upgrades, which were not. AC provision and energy efficiency can reinforce each other to bring considerable co-benefits, including in terms of thermal comfort. However, there are particular barriers to energy efficiency upgrades for rental housing, including split incentives, pay-off periods that exceed the time of expected residence, and a lack of information (Bird & Hernández, 2012; Palm & Reindl, 2018). Targeted programs and policies that overcome these barriers are particularly important given the energy cost burdens faced by low-income households in subsidized and market-rate housing (Kontokosta et al., 2020; Ray et al., 2019; Reina & Kontokosta, 2017). Utility cost assistance is one area where low-income households are the target audience, and expanded programs in this area would increase households' energy security and ability to cool their units (Murray & Mills, 2014).

Affordable housing in San José performs somewhat better than other multifamily housing, but there are still reasons to carefully consider the needs of these residents. The largest explanation is that affordable housing is much newer than other multifamily housing: the median year of construction for affordable housing developments was 1998, whereas it was 1961 for market-rate multifamily. Importantly, on some of our heat risk measures, the residents of affordable housing, like low-income residents of lower-cost unsubsidized housing, are likely more sensitive to heat (e.g., more seniors, children, underlying health conditions) and may have less adaptive capacity than other renters. Public housing may fare worse than other affordable housing due to

the age of construction and lack of federal funds; some advocacy groups have called on HUD to require that public housing authorities install or upgrade HVAC systems and include operating costs in utility allowances (Cohen et al., 2019; GHHI, 2020). Affordable housing funding programs can continue to increase energy efficiency standards, and a potential heat-specific model is California's Affordable Housing and Sustainable Communities (AHSC) program, which explicitly addresses extreme heat in its program criteria. However, we note that extreme heat is just one component of the program's "community climate resiliency" criteria, which itself constitutes 3% of the program's overall selection points (California Strategic Growth Council, 2021).

Our analysis points to several important areas for future research. First, there is a need for parcel-scale analyses of residential heat risk in different cities across climate regions. Fine-grained studies should connect housing and household characteristics, and their local context, with a broader understanding of urban thermal inequity. Parcel-scale analyses will allow us to identify variation within specific housing types and highlight potential case studies; for example, what can we learn from the most heat-resilient multifamily housing? Second, future research should incorporate additional outdoor temperature measures beyond LST that may better capture thermal comfort, such as air temperature and mean radiant temperature. Third, we need additional data and analyses related to indoor temperatures and energy use, particularly for low-income households. Although our study does estimate central AC availability, we do not know the extent to which households used AC or experienced financial trade-offs. Fourth, given that heat risk does not occur in isolation, there is an opportunity to study how residential heat risk intersects with exposure to air pollution and other environmental hazards. This is important because there are disparities in exposure to these hazards by race, ethnicity, and income, and potential interventions that could simultaneously address several hazards Lastly, although we did not focus on manufactured housing due to limitations of the assessor data, this is an important low-cost housing type that faces outsized exposure to heat hazards.

There are ample opportunities for local, state, and federal policymakers to increase residential heat resilience. Local governments should plan for and incentivize interventions that reduce heat risk, particularly for low-income renters (e.g., shade provision, energy efficiency programs, AC subsidies, utility assistance, "renters' right to AC" laws, cool roof incentives). Neighborhood-scale investments (e.g., parks, urban forestry) should be focused in low-income neighborhoods and communities of color. Additionally, cities should ensure that these investments do not contribute to "green gentrification," a potential unintended consequence of urban greening initiatives (Shokry et al., 2022). State governments should consider climate resilience when allocating the Low-Income Housing Tax Credit and offer supplemental funding for affordable housing developments that meet certain climate-related criteria; one potential model is California's AHSC program, as mentioned previously. HUD should assess heat risk for federally subsidized housing, explicitly incorporate heat resilience into program guidelines, and provide implementation funding. Lastly, Congress should expand AC provision for seniors and low-income households through Medicare and Medicaid, and sufficiently fund energy assistance programs to ensure that low-income households can afford to cool their homes.

Conclusions

In this study, we answered two questions for San José, California. First, how do heat risk measures vary by housing type and location in San José, California? Second, what housing and neighborhood factors are associated with greater heat risk? A combination of descriptive statistics, exploratory mapping, and regression analysis was used.

We found that there was more variation in our four heat risk measures by neighborhood than by housing type. Households facing the greatest heat risk lived in multifamily rental housing, whereas those with the least heat risk lived in detached single-family housing. The neighborhoods of San

José with the most heat risk were located in the central and eastern parts of the city, and heat risk tended to be associated with neighborhoods with more Hispanic/Latino and Asian residents.

This research has implications for urban scholarship and policy. For scholars, our research demonstrates the potential for using large-scale, parcel-based analyses to illuminate disparities in residential heat exposure. It also provides a foundation for additional research examining variation between and within housing types, along with households' experiences with heat. Local, state, and federal policymakers can reduce residential heat risk through the interventions described above.

Notes

1. In terms of attached housing, the assessor differentiates between apartments, which include multiple units on the same parcel, and townhouses/condos, for which each individual unit is assigned an individual parcel.
2. See Appendix Table A2 for a comparative analysis using a much cooler LST scene from September 29, 2021. This scene is 9°F cooler than the August scene, and represents the most complete dataset available with minimal cloud cover at a similar time of year, to minimize differences from solar incidence. We find consistent results across the two dates. From this we conclude that despite differences in LST due to meteorological conditions, relative spatial distribution and *z* scores are consistent for the purposes of this analysis.
3. We focus on central AC provision for conceptual and practical reasons. Conceptually, we focus on central AC because the literature shows it to have a greater connection with health outcomes. Practically, our models of window AC had very low sensitivity, meaning they were poor at identifying true negatives.
4. We addressed spatial dependence using OLS models with spatial fixed effects, rather than spatial regression models, for practical reasons. Spatial autocorrelation was indicated by Moran's *I* values, calculated on a 25% sample of parcels, ranging from 0.55 to 0.86 depending on the model. This calculation used a *k*-nearest neighbors spatial weights matrix ($k = 5$). Spatial regression models, however, proved to be computationally infeasible with the entire parcel dataset, even in a high-performance computing environment. The results of spatial lag models using this 25% random sample of parcels ($N = 53{,}000$) are shown in Appendix Table A3. The spatial lag results indicate modest differences from the OLS models, none of which would change the major findings from the analysis.
5. There is worse AC availability in public housing, due to factors described in the Discussion section, relative to other subsidized housing types. Data provided to us by the Santa Clara County Housing Authority indicated that of the agency's 2,193 units in San José, 32% had central AC, 44% had individual (window) AC, and 24% had no AC.
6. In a separate set of models, shown in Appendix Table A1, we substituted the neighborhood-level independent variables with Gabbe and Pierce's (2020) adaptive capacity and sensitivity index (ACSI), which includes 19 variables and had previously been used to analyze housing-related heat risk in California. There were only slight differences between the results shown in Table 3 and these models, and the ACSI index was not significantly associated with the heat risk variables across models.
7. This finding was different from much of the literature, and we use scatterplots to illustrate broadly negative tract-level relationships between income and heat risk factors in Figure A1.

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Disclosure Statement

No potential conflict of interest was reported by the author(s).

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References

Balbus, J. M., & Malina, C. (2009). Identifying vulnerable subpopulations for climate change health effects in the United States. *Journal of Occupational and Environmental Medicine*, *51*(1), 33–37. https://doi.org/10.1097/JOM.0b013e318193e12e

Baniassadi, A., & Sailor, D. J. (2018). Synergies and trade-offs between energy efficiency and resiliency to extreme heat–A case study. *Building and Environment*, *132*, 263–272. https://doi.org/10.1016/j.buildenv.2018.01.037

Berisha, V., Hondula, D., Roach, M., White, J. R., McKinney, B., Bentz, D., Mohamed, A., Uebelherr, J., & Goodin, K. (2017). Assessing adaptation strategies for extreme heat: A public health evaluation of cooling centers in Maricopa County, Arizona. *Weather, Climate, and Society*, *9*(1), 71–80. https://doi.org/10.1175/WCAS-D-16-0033.1

Bird, S., & Hernández, D. (2012). Policy options for the split incentive: Increasing energy efficiency for low-income renters. *Energy Policy*, *48*, 506–514. https://doi.org/10.1016/j.enpol.2012.05.053

Byrne, J., Ambrey, C., Portanger, C., Lo, A., Matthews, T., Baker, D., & Davison, A. (2016). Could urban greening mitigate suburban thermal inequity?: The role of residents' dispositions and household practices. *Environmental Research Letters*, *11*(9), 095014. https://doi.org/10.1088/1748-9326/11/9/095014

California Strategic Growth Council (2021). *AHSC round 6 guidelines*. https://www.hcd.ca.gov/grants-funding/active-funding/ahsc/docs/AHSC-Round-5-FY18-19-Guidelines.pdf

Chow, W. T. L., Chuang, W.-C., & Gober, P. (2012). Vulnerability to extreme heat in metropolitan Phoenix: Spatial, temporal, and demographic dimensions. *The Professional Geographer*, *64*(2), 286–302. https://doi.org/10.1080/00330124.2011.600225

City of New York (2021). Cooling assistance benefit. *NYC*. https://access.nyc.gov/programs/cooling-assistance-benefit/

City of San José (2012). *Tree canopy and land use classification*. *City of San José Enterprise GIS*. https://gisdata-csj.opendata.arcgis.com/pages/tree-canopy-and-land-use-classification

City of San José (2020). *Affordable rental housing*. https://data.sanjoseca.gov/dataset/affordable-rental-housing1

Cohen, D. A., Fleming, B., McDonald, K., Noisecat, J. B., Graetz, N., Lample, K., Lillehei, X., Paul, M., & Bahanda, A. (2019). A Green New Deal for American public housing communities. Data for Progress. https://www.filesforprogress.org/reports/green-new-deal-public-housing-national.pdf

Conlon, K. C., Mallen, E., Gronlund, C. J., Berrocal, V. J., Larsen, L., & O'Neill, M. S. (2020). Mapping human vulnerability to extreme heat: A critical assessment of heat vulnerability indices created using principal components analysis. *Environmental Health Perspectives*, *128*(9), 97001. https://doi.org/10.1289/EHP4030

Ellena, M., Breil, M., & Soriani, S. (2020). The heat-health nexus in the urban context: A systematic literature review exploring the socio-economic vulnerabilities and built environment characteristics. *Urban Climate*, *34*, 100676. https://doi.org/10.1016/j.uclim.2020.100676

Founda, D., & Santamouris, M. (2017). Synergies between urban heat island and heat waves in Athens (Greece), during an extremely hot summer (2012). *Scientific Reports*, *7*(1), 11. https://doi.org/10.1038/s41598-017-11407-6

Fraser, A. M., Chester, M. V., Eisenman, D., Hondula, D. M., Pincetl, S. S., English, P., & Bondank, E. (2017). Household accessibility to heat refuges: Residential air conditioning, public cooled space, and walkability. *Environment and Planning B: Urban Analytics and City Science*, *44*(6), 1036–1055. https://doi.org/10.1177/0265813516657342

Gabbe, C. J., & Pierce, G. (2020). Extreme heat vulnerability of subsidized housing residents in California. *Housing Policy Debate*, *30*(5), 843–860. https://doi.org/10.1080/10511482.2020.1768574

GHHI (2020). *Air conditioning, heat vulnerability, and racial equity*. Green & Healthy Homes Initiative. https://www.greenandhealthyhomes.org/wp-content/uploads/Air-Conditioning-Heat-Vulnerability-and-Racial-Equity.pdf

Gronlund, C. J. (2014). Racial and socioeconomic disparities in heat-related health effects and their mechanisms: A review. *Current Epidemiology Reports*, *1*(3), 165–173. https://doi.org/10.1007/s40471-014-0014-4

Gronlund, C. J., & Berrocal, V. J. (2020). Modeling and comparing central and room air conditioning ownership and cold-season in-home thermal comfort using the American Housing Survey. *Journal of Exposure Science & Environmental Epidemiology*, *30*(5), 814–823. https://doi.org/10.1038/s41370-020-0220-8

Harlan, S. L., Brazel, A. J., Prashad, L., Stefanov, W. L., & Larsen, L. (2006). Neighborhood microclimates and vulnerability to heat stress. *Social Science & Medicine (1982)*, *63*(11), 2847–2863. https://doi.org/10.1016/j.socscimed.2006.07.030

Harlan, S. L., Declet-Barreto, J. H., Stefanov, W. L., & Petitti, D. B. (2013). Neighborhood effects on heat deaths: Social and environmental predictors of vulnerability in Maricopa County, Arizona. *Environmental Health Perspectives*, *121*(2), 197–204. https://doi.org/10.1289/ehp.1104625

Hayden, M. H., Brenkert-Smith, H., & Wilhelmi, O. V. (2011). Differential adaptive capacity to extreme heat: A Phoenix, Arizona, case study. *Weather, Climate, and Society*, *3*(4), 269–280. https://doi.org/10.1175/WCAS-D-11-00010.1

Heaviside, C., Vardoulakis, S., & Cai, X. M. (2016). Attribution of mortality to the urban heat island during heatwaves in the West Midlands, UK. *Environmental Health*, *15*(S1), 49–59. https://doi.org/10.1186/s12940-016-0100-9

Hoffman, J. S., Shandas, V., & Pendleton, N. (2020). The effects of historical housing policies on resident exposure to intra-urban heat: A study of 108 U.S. urban areas. *Climate*, *8*(1), 12. https://doi.org/10.3390/cli8010012

Jenerette, G. D., Harlan, S. L., Buyantuev, A., Stefanov, W. L., Declet-Barreto, J., Ruddell, B. L., Myint, S. W., Kaplan, S., & Li, X. (2016). Micro-scale urban surface temperatures are related to land-cover features and residential heat related health impacts in Phoenix, AZ USA. *Landscape Ecology*, *31*(4), 745–760. https://doi.org/10.1007/s10980-015-0284-3

Jesdale, B. M., Morello-Frosch, R., & Cushing, L. (2013). The racial/ethnic distribution of heat risk–related land cover in relation to residential segregation. *Environmental Health Perspectives*, *121*(7), 811–817. https://doi.org/10.1289/ehp.1205919

Kenny, G. P., Flouris, A. D., Yagouti, A., & Notley, S. R. (2019). Towards establishing evidence-based guidelines on maximum indoor temperatures during hot weather in temperate continental climates. *Temperature (Austin, Tex.)*, *6*(1), 11–36. https://doi.org/10.1080/23328940.2018.1456257

Klinenberg, E. (2002). *Heat wave: A social autopsy of disaster in Chicago*. University of Chicago Press.

Kontokosta, C. E., Reina, V. J., & Bonczak, B. (2020). Energy cost burdens for low-income and minority households. *Journal of the American Planning Association*, *86*(1), 17–89. https://doi.org/10.1080/01944363.2019.1647446

Kuhn, M. (2020). caret: Classification and *regression training* (R package version 6.0-86) [Computer software]. https://CRAN.R-project.org/package=caret

Kuminoff, N. V., Parmeter, C. F., & Pope, J. C. (2010). Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? *Journal of Environmental Economics and Management*, *60*(3), 145–160. https://doi.org/10.1016/j.jeem.2010.06.001

Laaidi, K., Zeghnoun, A., Dousset, B., Bretin, P., Vandentorren, S., Giraudet, E., & Beaudeau, P. (2012). The impact of heat islands on mortality in Paris during the August 2003 heat wave. *Environmental Health Perspectives*, *120*(2), 254–259. https://doi.org/10.1289/ehp.1103532

Li, D., Sun, T., Liu, M., Yang, L., Wang, L., & Gao, Z. (2015). Contrasting responses of urban and rural surface energy budgets to heat waves explain synergies between urban heat islands and heat waves. *Environmental Research Letters*, *10*(5), 054009–054010. https://doi.org/10.1088/1748-9326/10/5/054009

Lumley, T. (2020). *survey: Analysis of complex survey samples* (R package version 4.0) [Computer software]. https://cran.r-project.org/web/packages/survey/survey.pdf

Macintyre, H. L., & Heaviside, C. (2019). Potential benefits of cool roofs in reducing heat-related mortality during heatwaves in a European city. *Environment International*, *127*, 430–441. https://doi.org/10.1016/j.envint.2019.02.065

Madrigano, J., Lane, K., Petrovic, N., Ahmed, M., Blum, M., & Matte, T. (2018). Awareness, risk perception, and protective behaviors for extreme heat and climate change in New York City. *International Journal of Environmental Research and Public Health*, *15*(7), 1433. https://doi.org/10.3390/ijerph15071433

Mavrogianni, A., Wilkinson, P., Davies, M., Biddulph, P., & Oikonomou, E. (2012). Building characteristics as determinants of propensity to high indoor summer temperatures in London dwellings. *Building and Environment*, *55*, 117–130. https://doi.org/10.1016/j.buildenv.2011.12.003

Meade, R. D., Akerman, A. P., Notley, S. R., McGinn, R., Poirier, P., Gosselin, P., & Kenny, G. P. (2020). Physiological factors characterizing heat-vulnerable older adults: A narrative review. *Environment International*, *144*, 105909.

Mitchell, B. C., & Chakraborty, J. (2014). Urban heat and climate justice: A landscape of thermal inequity in Pinellas County, Florida. *Geographical Review*, *104*(4), 459–480. https://doi.org/10.1111/j.1931-0846.2014.12039.x

Mitchell, B. C., & Chakraborty, J. (2015). Landscapes of thermal inequity: Disproportionate exposure to urban heat in the three largest U.S. cities. *Environmental Research Letters*, *10*(11), 115005. https://doi.org/10.1088/1748-9326/10/11/115005

Murray, A. G., & Mills, B. F. (2014). The impact of low-income home energy assistance program participation on household energy insecurity. *Contemporary Economic Policy*, *32*(4), 811–825. https://doi.org/10.1111/coep.12050

Nahlik, M. J., Chester, M. V., Pincetl, S. S., Eisenman, D., Sivaraman, D., & English, P. (2017). Building thermal performance, extreme heat, and climate change. *Journal of Infrastructure Systems*, *23*(3), 04016043. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000349

National Weather Service (2018). Weather related fatality and injury statistics. https://www.weather.gov/hazstat/

NOAA (2020). *Climate data online*. National Oceanic and Atmospheric Administration. https://www.ncdc.noaa.gov/cdo-web/

O'Neill, M. S., Zanobetti, A., & Schwartz, J. (2005). Disparities by race in heat-related mortality in four U.S. cities: The role of air conditioning prevalence. *Journal of Urban Health: bulletin of the New York Academy of Medicine*, *82*(2), 191–197. https://doi.org/10.1093/jurban/jti043

Ostro, B., Rauch, S., Green, R., Malig, B., & Basu, R. (2010). The effects of temperature and use of air conditioning on hospitalizations. *American Journal of Epidemiology*, *172*(9), 1053–1061. https://doi.org/10.1093/aje/kwq231

Palm, J., & Reindl, K. (2018). Understanding barriers to energy-efficiency renovations of multifamily dwellings. *Energy Efficiency*, *11*(1), 53–65. https://doi.org/10.1007/s12053-017-9549-9

Pearsall, H. (2017). Staying cool in the compact city: Vacant land and urban heating in Philadelphia, Pennsylvania. *Applied Geography*, *79*, 84–92. https://doi.org/10.1016/j.apgeog.2016.12.010

Peel, M. C., Finlayson, B. L., & McMahon, T. A. (2007). Updated world map of the Köppen-Geiger climate classification. *Hydrology and Earth System Sciences*, *11*(5), 1633–1644. https://doi.org/10.5194/hess-11-1633-2007

Perl, L. (2014). LIHEAP: Program and *funding*. Congressional Research Service. https://www.ncsl.org/portals/1/documents/cyf/liheapprogramfunding.pdf

Quandt, S. A., Wiggins, M. F., Chen, H., Bischoff, W. E., & Arcury, T. A. (2013). Heat index in migrant farmworker housing: Implications for rest and recovery from work-related heat stress. *American Journal of Public Health*, *103*(8), e24–e26. https://doi.org/10.2105/AJPH.2012.301135

Quinn, A., Kinney, P., & Shaman, J. (2017). Predictors of summertime heat index levels in New York City apartments. *Indoor Air*, *27*(4), 840–851. https://doi.org/10.1111/ina.12367

Ray, A., Wang, R., Nguyen, D., Martinez, J., Taylor, N., & Searcy, J. K. (2019). Household energy costs and the housing choice voucher program: Do utility allowances pay the bills? *Housing Policy Debate*, *29*(4), 607–626. https://doi.org/10.1080/10511482.2019.1566158

Reid, C. E., O'Neill, M. S., Gronlund, C. J., Brines, S. J., Brown, D. G., Diez-Roux, A. V., & Schwartz, J. (2009). Mapping community determinants of heat vulnerability. *Environmental Health Perspectives*, *117*(11), 1730–1736. https://doi.org/10.1289/ehp.0900683

Reina, V. J., & Kontokosta, C. (2017). Low hanging fruit? Regulations and energy efficiency in subsidized multifamily housing. *Energy Policy*, *106*, 505–513. https://doi.org/10.1016/j.enpol.2017.04.002

Rigolon, A. (2016). A complex landscape of inequity in access to urban parks: A literature review. *Landscape and Urban Planning*, *153*, 160–169. https://doi.org/10.1016/j.landurbplan.2016.05.017

Rogot, E., Sorlie, P. D., & Backlund, E. (1992). Air-conditioning and mortality in hot weather. *American Journal of Epidemiology*, *136*(1), 106–116. https://doi.org/10.1093/oxfordjournals.aje.a116413

Rosenthal, J., Kinney, P., & Metzger, K. (2014). Intra-urban vulnerability to heat-related mortality in New York City, 1997–2006. *Health & Place*, *30*, 45–60. https://doi.org/10.1016/j.healthplace.2014.07.014

Ruuhela, R., Votsis, A., Kukkonen, J., Jylhä, K., Kankaanpää, S., & Perrels, A. (2020). Temperature-related mortality in Helsinki compared to its surrounding region over two decades, with special emphasis on intensive heatwaves. *Atmosphere*, *12*(1), 13–46. https://doi.org/10.3390/atmos12010046

Samuelson, H., Baniassadi, A., Lin, A., Izaga González, P., Brawley, T., & Narula, T. (2020). Housing as a critical determinant of heat vulnerability and health. *The Science of the Total Environment*, *720*, 137296. https://doi.org/10.1016/j.scitotenv.2020.137296

Sanders, B., Ocasio-Cortez, A. (2021). The *green new deal* for Public Housing Act. https://www.sanders.senate.gov/wp-content/uploads/GND-PUBLIC-HOUSING-ACT-Section-by-Section-117th-FINAL.pdf

Shokry, G., Anguelovski, I., Connolly, J. J. T., Maroko, A., & Pearsall, H. (2022). "They didn't see it coming": Green resilience planning and vulnerability to future climate gentrification. *Housing Policy Debate*, *32*(1), 211–235. https://doi.org/10.1080/10511482.2021.1944269

Stone, B., Mallen, E., Rajput, M., Broadbent, A., Krayenhoff, E. S., Augenbroe, G., & Georgescu, M. (2021). Climate change and infrastructure risk: Indoor heat exposure during a concurrent heat wave and blackout event in Phoenix, Arizona. *Urban Climate*, *36*, 100787. https://doi.org/10.1016/j.uclim.2021.100787

Stone, B., Mallen, E., Rajput, M., Gronlund, C. J., Broadbent, A. M., Krayenhoff, E. S., Augenbroe, G., O'Neill, M. S., & Georgescu, M. (2021). Compound climate and infrastructure events: How electrical grid failure alters heat wave risk. *Environmental Science & Technology*, *55*(10), 6957–6964. https://doi.org/10.1021/acs.est.1c00024

Taylor, J., Wilkinson, P., Davies, M., Armstrong, B., Chalabi, Z., Mavrogianni, A., Symonds, P., Oikonomou, E., & Bohnenstengel, S. I. (2015). Mapping the effects of urban heat island, housing, and age on excess heat-related mortality in London. *Urban Climate*, *14*, 517–528. https://doi.org/10.1016/j.uclim.2015.08.001

Tsoulou, I., Andrews, C. J., He, R., Mainelis, G., & Senick, J. (2020). Summertime thermal conditions and senior resident behaviors in public housing: A case study in Elizabeth, NJ, USA. *Building and Environment*, *168*, 106411. https://doi.org/10.1016/j.buildenv.2019.106411

Uejio, C. K., Wilhelmi, O. V., Golden, J. S., Mills, D. M., Gulino, S. P., & Samenow, J. P. (2011). Intra-urban societal vulnerability to extreme heat: The role of heat exposure and the built environment, socioeconomics, and neighborhood stability. *Health & Place*, *17*(2), 498–507. https://doi.org/10.1016/j.healthplace.2010.12.005

United States Census Bureau (2017). *American housing survey*. http://www.census.gov/programs-surveys/ahs.html

U.S. Bureau of Labor Statistics. (2020). *American time use survey*. https://www.bls.gov/tus/

U.S. Census Bureau (2019). *2015–2019 American Community Survey 5-year estimates*. U.S. Bureau of the Census. https://www.census.gov/programs-surveys/acs

U.S. Department of Energy (2015). *Guide to determining climate regions by county*. U.S. Department of Energy Building Technologies Office. https://www.energy.gov/sites/default/files/2015/10/f27/ba_climate_region_guide_7.3.pdf

U.S. Department of Housing and Urban Development. (2014). *Climate change adaptation plan*. U.S. Department of Housing & Urban Development. https://www.hud.gov/sites/documents/HUD2014CCADAPTPLAN.PDF
U.S. EPA (2006). *Excessive heat events guidebook*. https://www.epa.gov/sites/default/files/2016-03/documents/ehe-guide_final.pdf
U.S. EPA, & CDC (2016). *Climate change and extreme heat: What you can do to prepare (EPA 430-R-16-061)*. U.S. Environmental Protection Agency (EPA) & Centers for Disease Control and Prevention (CDC). https://www.cdc.gov/climateandhealth/pubs/extreme-heat-guidebook.pdf
USGS (2021). Landsat data access. U.S. Geological Survey. https://www.usgs.gov/core-science-systems/nli/landsat/landsat-data-access?qt-science_support_page_related_con=0#qt-science_support_page_related_con
Voelkel, J., Hellman, D., Sakuma, R., & Shandas, V. (2018). Assessing vulnerability to urban heat: A study of disproportionate heat exposure and access to refuge by socio-demographic status in Portland, Oregon. *International Journal of Environmental Research and Public Health*, *15*(4), 640. https://doi.org/10.3390/ijerph15040640
Walker, L. A. (2015). The cost of good intentions: Thermal discomfort in traditional public housing units with preset thermostats. *Housing Policy Debate*, *25*(1), 152–178. https://doi.org/10.1080/10511482.2014.924024
White-Newsome, J. L., Sánchez, B. N., Jolliet, O., Zhang, Z., Parker, E. A., Dvonch, J. T., & O'Neill, M. S. (2012). Climate change and health: Indoor heat exposure in vulnerable populations. *Environmental Research*, *112*, 20–27. https://doi.org/10.1016/j.envres.2011.10.008
Wilhelmi, O. V., & Hayden, M. H. (2010). Connecting people and place: A new framework for reducing urban vulnerability to extreme heat. *Environmental Research Letters*, *5*(1), 014021. 014021. https://doi.org/10.1088/1748-9326/5/1/014021
Wilson, B. (2020). Urban heat management and the legacy of redlining. *Journal of the American Planning Association*, *86*(4), 415–443. https://doi.org/10.1080/01944363.2020.1759127
Wilson, B., & Chakraborty, A. (2019). Mapping vulnerability to extreme heat events: Lessons from metropolitan Chicago. *Journal of Environmental Planning and Management*, *62*(6), 1024–1065. https://doi.org/10.1080/09640568.2018.1462475
Wolch, J., Wilson, J. P., & Fehrenbach, J. (2005). Parks and park funding in Los Angeles: An equity-mapping analysis. *Urban Geography*, *26*(1), 4–35. https://doi.org/10.2747/0272-3638.26.1.4
Wright, M. K., Hondula, D. M., Chakalian, P. M., Kurtz, L. C., Watkins, L., Gronlund, C. J., Larsen, L., Mallen, E., & Harlan, S. L. (2020). Social and behavioral determinants of indoor temperatures in air-conditioned homes. *Building and Environment*, *183*, 107187. https://doi.org/10.1016/j.buildenv.2020.107187
Yardley, J., Sigal, R. J., & Kenny, G. P. (2011). Heat health planning: The importance of social and community factors. *Global Environmental Change*, *21*(2), 670–679. https://doi.org/10.1016/j.gloenvcha.2010.11.010
Zillow (2022). *San Jose home values*. https://www.zillow.com/san-jose-ca/home-values/

Appendix 1

Table A1. Regression of heat risk factors on parcel housing and neighborhood adaptive capacity and sensitivity index (ACSI) (ordinary least squares models).

	(1)	(2)	(3)	(4)
	% parcel without tree canopy	Land surface temp. (°F) on August 9, 2020	Prob. of no central AC	Heat risk index
Attached owner	−0.042*** (0.007)	−0.940*** (0.241)	0.224*** (0.002)	1.209*** (0.075)
Attached rental (market-rate)	0.004 (0.004)	0.822*** (0.146)	0.216*** (0.004)	1.523*** (0.062)
Attached rental (affordable)	−0.007 (0.009)	0.482 (0.259)	0.219*** (0.004)	1.617*** (0.091)
Housing units on parcel	−0.0001** (0.00004)	−0.003** (0.001)	0.00002 (0.00001)	−0.001* (0.0003)
Year of construction	0.001*** (0.0002)	−0.007 (0.005)	−0.007*** (0.0001)	−0.039*** (0.001)
ACSI	−0.002 (0.002)	−0.046 (0.080)	0.00003 (0.001)	−0.011 (0.026)
Fixed effects	Zip code	Zip code	Zip code	Zip code
No. of observations	212,336	212,336	212,336	212,336
Adjusted R^2	0.262	0.433	0.961	0.616
Residual standard error ($df = 212{,}293$)	0.066	2.245	0.03	0.752

Note. AC = air conditioning. The reference group for the categorical housing variable is detached single-family.
*$p < .05$. **$p < .01$. ***$p < .001$.

Table A2. Regression of land surface temperature (°F) from September 29, 2021 on parcel housing and neighborhood characteristics (ordinary least squares models).

	Land surface temp. (°F) on August 9, 2020	
	(1)	(2)
Attached owner	−1.204*** (0.017)	−0.904*** (0.221)
Attached rental (market-rate)	1.758*** (0.029)	0.684*** (0.135)
Attached rental (affordable)	0.006 (0.185)	−0.086 (0.227)
Housing units on parcel		−0.004*** (0.001)
Year of construction		−0.006 (0.004)
Pop. per sq. mi (1,000 s)		0.051* (0.024)
Pop. under 5 years (proportion)		1.761 (6.013)
Pop. over 65 years (proportion)		2.018 (2.393)
Median household income (1,000 s)		−0.011** (0.004)
Renter households (proportion)		−1.842** (0.650)
Black pop. (proportion)		−4.884 (4.286)
Hispanic pop. (proportion)		4.168** (1.322)
Asian pop. (proportion)		2.728* (1.144)
Fixed effects	Zip code	Zip code
No. of observations	212,336	212,336
R^2	0.043	0.538
Adjusted R^2	0.043	0.537
Residual standard error	2.751 ($df = 212,332$)	1.913 (df = 212,286)
F statistic	3,216.045*** ($df = 3$; 212,332)	

Note. The reference group for the categorical housing variable is detached single-family.
*$p < .05$. **$p < .01$. ***$p < .001$.

Table A3. Regression of heat risk factors on parcel housing and neighborhood characteristics (spatial lag models on a 25% sample of parcels).

	% parcel without tree canopy		Land surface temp. (°F) on August 9, 2020		Prob. of no central AC		Heat risk index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attached owner	−0.003*** (0.0004)	−0.007*** (0.0005)	−0.101*** (0.010)	−0.111*** (0.011)	0.023*** (0.001)	0.199*** (0.0005)	0.102*** (0.007)	0.671*** (0.008)
Attached rental (market-rate)	0.001* (0.001)	0.003*** (0.001)	0.098*** (0.016)	0.130*** (0.017)	0.121*** (0.002)	0.196*** (0.001)	0.724*** (0.013)	0.865*** (0.011)
Attached rental (affordable)	0.026*** (0.004)	0.030*** (0.005)	0.095 (0.103)	0.159 (0.110)	−0.037*** (0.011)	0.188*** (0.004)	0.115 (0.080)	0.984*** (0.070)
Housing units on parcel		−0.0001*** (0.00002)		−0.0005 (0.0004)		0.00001 (0.00001)		−0.001** (0.0003)
Year of construction		0.0002*** (0.00001)		−0.0004 (0.0002)		−0.006*** (0.00001)		−0.025*** (0.0002)
Pop. per sq. mi (1,000 s)		−0.0002*** (0.00005)		0.009*** (0.001)		−0.0003*** (0.00004)		−0.003*** (0.001)
Pop. under 5 years (proportion)		0.026* (0.011)		1.489*** (0.275)		0.075*** (0.010)		1.545*** (0.173)
Pop. over 65 years (proportion)		−0.015** (0.005)		0.090 (0.118)		0.005 (0.004)		0.192** (0.074)
Median household income (1,000 s)		0.00001 (0.00001)		−0.001*** (0.0002)		0.0001*** (0.00001)		0.0003* (0.0001)
Renter households (proportion)		−0.0002 (0.002)		−0.256*** (0.037)		−0.003 (0.001)		−0.151*** (0.023)
Black pop. (proportion)		−0.010 (0.008)		0.136 (0.186)		−0.040*** (0.007)		0.063 (0.118)
Hispanic pop. (proportion)		0.020*** (0.002)		0.782*** (0.058)		0.015*** (0.002)		0.933*** (0.037)
Asian pop. (proportion)		0.017*** (0.002)		0.642*** (0.050)		0.004* (0.002)		1.135*** (0.032)
Fixed effects	None	ZIP code	None	ZIP code	None	ZIP code	None	ZIP code
No. of observations	53,000	53,000	53,000	53,000	53,000	53,000	53,000	53,000
Log likelihood	101,385.10	102,251.90	−69,157.13	−68,006.72	55,648.01	114,199.40	−52,278.43	−39,103.69
sigma2	0.001	0.001	0.577	0.58	0.006	0.001	0.347	0.232
AIC	−202,758.20	−204,401.80	138,326.30	136,115.40	−111,284.00	−228,296.90	104,568.90	78,309.39
Wald test (df = 1)	343,500.800***	221,047.400***	1,047,673.000***	485,045.900***	117,236.300***	8,376.152***	158,868.400***	66,683.920***
LR test (df = 1)	81,524.490***	65,014.290***	125,749.700***	92,853.230***	53,616.790***	8,014.751***	60,177.540***	38,067.820***

Note. AC = air conditioning. AIC = Akaike information criterion. LR: Likelihood ratio. The reference group for the categorical housing variable is detached single-family.
*$p < .05$. **$p < .01$. ***$p < .001$.

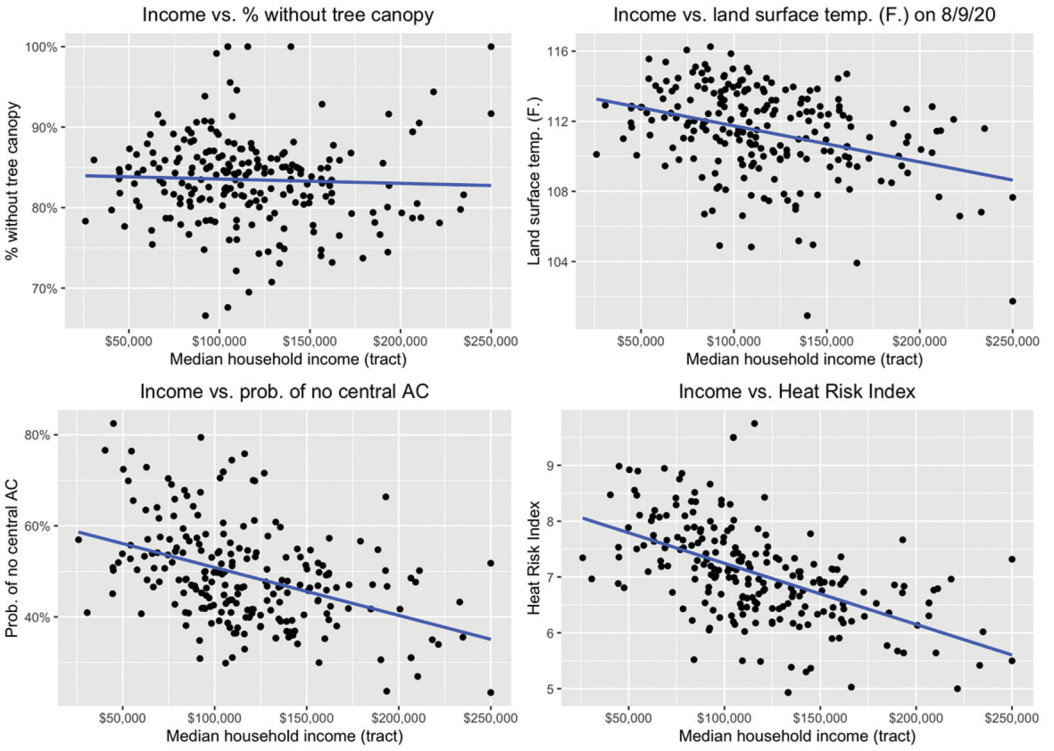


Figure A1. Relationships between median household income and tract-average heat risk factors.