NBER WORKING PAPER SERIES

THE URBAN CRIME AND HEAT GRADIENT IN HIGH AND LOW POVERTY AREAS

Kilian Heilmann
Matthew E. Kahn

Working Paper 25961
http://www.nber.org/papers/w25961

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2019

We are grateful for helpful comments by seminar participants at Johns Hopkins University, the University of Southern California, the Southern California Conference on Applied Microeconomics, and the European Meeting of the Urban Economics Association. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Urban Crime and Heat Gradient in High and Low Poverty Areas
Kilian Heilmann and Matthew E. Kahn
NBER Working Paper No. 25961
June 2019
JEL No. H41,Q53,Q54

ABSTRACT

We use spatially disaggregated daily crime data for the City of Los Angeles to measure the impact of heat and pollution on crime and to study how this relationship varies across the city. On average, overall crime increases by 2.2% and violent crime by 5.7% on days with maximum daily temperatures above 85 degrees Fahrenheit (29.4° C) compared to days below that threshold. The heat-crime relationship is more pronounced in low-income neighborhoods. This suggests that heat shocks can increase spatial urban quality of life differences through their effect on crime. We use other administrative data and find some evidence that policing intensity declines on extremely hot days. These findings highlight that the quality of urban governance during times of extreme stress may be an important policy lever in helping all socio-economic groups adapt to climate change.

Kilian Heilmann
University of Southern California
Dornsife Institute for New Economic Thinking
3620 South Vermont Avenue
Los Angeles, CA 90089
USA
heilmann@usc.edu

Matthew E. Kahn
Department of Economics
University of Southern California
KAP
Los Angeles, CA 90089
and NBER
kahnme@usc.edu

1 Introduction

Climate change is predicted to increase global temperatures by 2.5 to 10 degrees Fahrenheit over the next century and to cause more extremely hot days (Nakicenovic et al., 2000). Heat has been linked to several negative effects ranging from increasing mortality (Barreca et al., 2016) to decreasing productivity (Zhang et al., 2018) and test scores (Goodman et al., 2018). A recent climate economics literature has documented the effects of temperature extremes on crime and violence. These studies measure the association between climate and aggressive behavior. Behavioral reactions to heat range from civil conflict (Burke et al., 2009; Hsiang et al., 2013; Burke et al., 2015) to temperament (Baylis, 2015) and crime (Ranson, 2014; Bruederle et al., 2017). Researchers use their econometric estimates of the violence/temperature gradient combined with climate change forecast models to predict the excess violence that might occur in the future due to climate change.

If such predictions could be downscaled to make within city predictions, it is likely to be the case that the greatest crime growth brought about by climate change induced heat would occur in the poorest parts of cities. While crime rates have fallen sharply over the last 30 years across major U.S cities, crime continues to be a major threat to urban quality of life (Levitt, 2004; Nilsson and Estrada, 2006; Galster and Sharkey, 2017). In major American cities such as Chicago and Washington, DC, crime is highly spatially concentrated in high poverty areas creating large differences of life quality between neighborhoods (O'Flaherty and Sethi, 2010; Massey and Denton, 1993). These areas tend to be home to African-American and Hispanic populations who live in older, lower quality housing (DiPasquale and Kahn, 1999) while affluent neighborhoods are shielded from crime exposure.

We expect that poor people who live in the poorest neighborhoods in cities will have the least ability to adapt to new risks they face due to climate change. This means that climate change will increase quality of life inequality across neighborhoods. While it is well known that the costs of climate change are unequally distributed towards poorer countries and regions within countries, little is known about distributional effects over smaller space *within* cities.[1] How will the rise in temperatures affect urban crime patterns through its impact on crime and how will it change the quality of life disparity within cities? We shed light on this question by analyzing crime over space within a major city.

[1] A notable early exception is Harries et al. (1984) who study trends in summer assaults by neighborhood socioeconomic status for a single year in Dallas, Texas.

Past research on urban quality of life has measured differences in cross-city quality of life over the course of an entire year (Gyourko and Tracy, 1991) or across large geographic areas such as Census PUMAs (DiPasquale and Kahn, 1999). An innovation in this paper is that we explore fine spatial variation in quality of life dynamics within a city across its various neighborhoods. Using newly available administrative data from the City of Los Angeles, this paper melds insights from the crime and poverty literature with the literature on heat and crime.

Newly available geocoded administrative data on all crime reports in the City of Los Angeles over the years 2010 to 2017 allow us to estimate local responses to extreme weather and link these estimates to neighborhood characteristics. We first use variation in temperatures over time and space to estimate heat-crime gradients in Los Angeles. We find that heat has a statistically significant effect on crime incidents, especially violent crime. On average, extremely hot days with maximum temperatures above 85 Fahrenheit lead to a an increase of general crime of 2.2% and 5.7% in violent crime. We then match geocoded crime events to neighborhood characteristics to investigate whether this relationship varies over space. This allows us to test the hypothesis that crime disproportionally increases in high poverty areas on extremely hot days. We find evidence consistent with this hypothesis with effects fifty times as large in the interquartile range. Since richer people have greater access to self protection strategies, quality of life in poorer neighborhoods declines by more than it does in richer areas. This implies that extreme weather shocks can exacerbate urban inequality in quality of life and that the crime burden of climate change is unequally distributed towards already disadvantaged neighborhoods.

We next explore the determinants of the differential burden. We find steeper heat-crime gradients in communities with an older housing stock. Exploiting the rich detail of our crime data, we document that this effect is especially strong for domestic crimes and violence against intimate partners, both types of crimes which are typically committed at home. We interpret this as a result of a lack of heat-mitigation due to the higher cost of adaptation (e.g. through the use of air conditioning) in older buildings. This suggests that the built-up environment is a key driver for climate change adaptation. We rule out other behavioral mechanisms such as differences in police deterrence. Using internal police communication data, we analyze the government's response towards heat induced crime and test the hypothesis that the police devote less effort on extremely hot days. Although active investigations of police officers in patrol cars decrease at higher temperatures, we do not observe differential effects over space that could explain the unequal crime response to heat.

Our paper builds upon a recent environmental economics literature that studies how short-term fluctuations in the environment influence crime. Ranson (2014) estimates a positive medium-run heat-crime gradients using quarterly crime and temperature data at the county level in the US. Bruederle et al. (2017) find a similar positive association in South Africa. Using finer spatial level data, Herrnstadt et al. (2016) investigate the effect of ambient air pollution on criminal activity in Los Angeles and Chicago. These studies have shown that climate plays a significant role in driving criminal behavior. Our study also contributes to research in urban economics and sociology analyzing how crime varies across space and examining the correlates of crime levels across cities and counties (Sampson, 1986; Kposowa and Breault, 1993). In our study, we document that the heat-crime relationship varies as a function of neighborhood income and housing age. We further connect these findings to recent research that has examined the quality of governance under stressful climate conditions. Obradovich et al. (2018) and Heyes and Saberian (2018) document that heat exposure leads to reduced activity of regulators such as food safety inspectors and traffic police officers, and can influence high-stake decisions of immigration court judges even in climate-controlled settings.

The paper is structured as follows: Section 2 discusses the theoretical foundations of the heat-crime relationship. Section 3 describes the sources of our data in detail while Section 4 highlights the estimation strategy. Section 5 discusses our empirical results for the heat-crime relationship and Section 6 looks at the city government response to heat. Section 7 concludes.

2 The Conceptional Framework

In this study, we estimate heat-crime gradients and test whether they vary by neighborhood socioeconomic characteristics. We first establish a conceptual framework to distinguish channels that can create this reduced form effect and why we would expect that this relationship varies by space. We distinguish between direct physiological reactions and changes in the environment that cause behavioral reactions.

The first channel that links heat to increases in crime is a physiological process where one's mental capacity is reduced. Extreme heat can lead to reduced self-control and then translate into criminal behavior. Several studies on the physiological channel have found evidence for increases in aggression and violent behavior in controlled settings when study subjects are exposed to high temperatures (Baron and Bell, 1976; Vrij et al., 1994; Boyanowsky, 1999; Anderson et al., 2000). Thermal stress might also alter individuals' internal mental decision process more indirectly through changes in risk aversion and time preferences that then lead to changes in asocial behavior. A recent large scale laboratory study on extreme heat's influence on cognitive components found little impact on these factors, but documented an increase in the joy of destruction at high temperatures (Almås et al., 2019).

It is unclear to what extent these isolated physiological reactions translate into actual societal outcomes such as crime in a more complex real-world setting outside the laboratory. The effects could either be immediate or mediated by other physical reactions such as the inability to sleep on hot days. This itself could lead to an increase in irritation and aggression, and ultimately cause people to commit crime (Laibson, 2001; Heller et al., 2017; Anderson, 2001).

Poorer people have fewer resources to invest in self protection to reduce their exposure to the heat. They live in older, lower quality housing and are less able to afford strategies for achieving climate control. We recognize that each day, people allocate their time between being in private spaces such as a home or a workplace and public spaces (i.e outside or at a public school). Recent research has documented that poorer and minority children are more likely to attend schools that do not have air conditioning and thus are more susceptible to the negative effects of the heat.(Goodman et al., 2018).

An alternative hypothesis that connects heat and crime is linked to the work of Becker (1968) and focuses on the external factors that rational agents face. Risk neutral individuals will be more likely to engage in crime when the expected benefits exceed the expected costs. The probability of being arrested could be a function of temperature. The likelihood of being punished for a crime is direct function of police deterrence and will be lower if the police reduce their patrolling on hot days.[2] Given that the police are paid a fixed hourly salary, if effort is more costly on hot days then a simple principal/agent model would predict that they will devote less effort on days when it is more comfortable to remain in an air conditioned office or police car. Recent empirical evidence shows reduced effort of government agencies in low-stake tasks such as traffic controls on warmer days (Obradovich et al., 2018) and it is plausible that this pattern persists for general crime deterrence.

[2]In this simple model, we do not allow the level of punishment to vary by temperature. While a recent literature has documented sizable effects of climatic factors on judges' decisions (Heyes and Saberian, 2018; Kahn and Li, 2019), these effects are present during the time of the decision and not during the time of the crime. These times are unpredictable and therefore not in the information set of the rational criminal.

In our empirical analysis, we use several datasets to test whether the patterns in the data are consistent with these mechanisms. The relative importance of each mechanism is crucial for policy makers to design appropriate policies. Our crime data provide detailed information on crime categories. We hypothesize that the mechanisms above imply differential predictions for different crime categories. We will distinguish crime categories by their monetary reward and their ability to be deterred. We will further use internal police communication data to explore whether public sector workers exert less effort on extremely hot days.

We recognize that there are other pathways through which heat can influence crime. Warmer days could increase the interaction between people and thus create more opportunities to commit crimes. For example, on warmer days people are out more and thus interact more with each other. This might lead to an increase in random altercations or opportunity crime. We address this effect by controlling for measures of aggregate city activity proxied by the amount of vehicle traffic.

3 The Data

This section introduces the setting of our study, describes the sources of our data and presents summary statistics of key variables used in the econometric analysis.

3.1 Study Setting and Crime Data

This paper's empirics are based on digitized crime reports, arrest counts, and service call records processed and provided by the Los Angeles Police Department (LAPD). The Los Angeles Police Department is the third biggest police department in the United States after the agencies in New York and Chicago, and polices the over four million residents and many more commuters in the City of Los Angeles.[3] We choose to focus on Los Angeles because the city features large variation in demographic and socioeconomic characteristics. Unlike older cities that often feature a prominent division between poor, crime-prone inner cities and affluent, low-crime suburbs with separate police departments, the jurisdiction of LAPD is home to people of all races and backgrounds.

[3]While the City of Los Angeles makes up a large part of the metropolitan area, certain parts of the metropolitan area are not observed as neighboring cities have their own police force (i.e. Beverly Hills) or have their police service contracted through the County of Los Angeles.

To measure crime activity, we use detailed crime reports made public through the city's open data portal. The main dataset covers an eight year period from 2010-2017 and comprises 1.7 million crime incidents in the City of Los Angeles. These digitized police reports have been transcribed from the original crime reports and contain a variety of background information on each crime with unrivaled detail. The dataset provides the time and date the crime occurred and was reported, the type of crime, the exact geocoded location with premise description, weaponry used, as well as demographics of the victims. In addition to the general crime statistics, we draw from another dataset provided by LAPD that highlights those crimes that were committed against homeless people. These data are only available for a shorter reporting period from August 2016 to August 2017.

The geographic unit of analysis are 1,288 police reporting districts within the City of Los Angeles. These reporting districts are used for statistics and mapping purposes by the police and reflect areas of similar demographic and socioeconomic characteristics. We aggregate counts of different crime types at this level and create a daily panel dataset of neighborhood crime activity, thus treating reporting districts as independent unit of observations in our regression setup. Reporting district boundaries are often congruous with census tracts, which we will exploit to link crime locations with neighborhood characteristics from the American Community Survey. Our study area including the police reporting boundaries is depicted in Figure 1.

To link crime activity with the measures of intensity of the police response towards it, we augment the main crime data with additional LAPD datasets. To measure police effort, we use data on the universe of LAPD calls requesting service over the same time period as the crime reports. For each police investigation, LAPD creates a call of service record. These call records are tagged with location identifiers, a detailed timestamp and a call type code. We use the most common call type code *Code 6* denoting the arrival of a police unit and the start of an active investigation. We have also collected other measures of police activity including geocoded traffic stops for both vehicles and pedestrians. This dataset contains the time of the traffic stop, demographics on the stopped person, and a police officer identification number. We augment this dataset with data on arrests. For each booking between 2010 and 2017, we observe the time of the arrest, a description of the charge, the geocoded location, and the age, sex, and race demographics of the arrestee.

Taken together, these datasets provide an unprecedented picture of crime and police activity in a major city. While we observe these detailed policing data, we are unable to measure certain aspects of quality and efficiency of policing services. For example, we do not possess information on unanswered service request calls or data on the number of patrolling police officers each day.[4] Thus, while our data can inform us of the extensive margin of the interplay between crime dynamics and heat shocks in Los Angeles, it is a less conclusive indicator of climate's effect at the intensive margin.

3.1.1 Weather and Pollution Data

To implement our empirical strategy, we spatially link our geocoded crime data with climatic variables from different reporting agencies. We obtain temperature data from the National Climatic Data Center (NCDC) administered by the National Oceanic and Atmospheric Administration (NOAA). We use the daily summaries on atmospheric characteristics from the Global Historical Climate Network product. From this dataset, we retrieve daily temperature maximums and minimums, the amount of precipitation, snowfall, and windspeed for the weather stations located within and near the Los Angeles metropolitan area. We use different interpolation methods to link neighborhood level crime with climate data that is measured at a more granular resolution.

We augment this data with measures on air quality. Air pollution has been identified as a major influence on human behavior including crime (Rotton and Frey, 1985; Chen and Schwartz, 2009; Ailshire and Crimmins, 2014). Recent studies have established causal evidence that fine particular matter in the air can lead to increases in urban crime (Herrnstadt et al., 2016). To measure pollution, we use readings from the Air Quality Index (AQI) monitors scattered around Los Angeles. We focus on one particular pollutant, namely particulate matter with diameter of less than 2.5 micrometers (PM2.5). While the air quality monitors provide measurements on other indicators, we focus on PM2.5 as the main proxy for air quality.[5] PM2.5 is produced by motor vehicles, power plants and other sources, and has been shown to strongly correlate with health conditions (Currie et al., 2009).

[4] The LAPD explicitly states on its webpage that the agency does not reply to academic requests for data.

[5] Another main pollutant is ozone which is created by chemical reaction with oxygen molecules and sunlight, and therefore driven by temperature. Including a measure of ozone in our regression would lead to a partial effect of temperature alone on crime while our estimates capture the entire net effect.

3.1.2 Socioeconomic and Traffic Data

In order to correlate the heat-crime relationship with neighborhood characteristics at the crime location, we use data from the American Community Survey at the census tract level. We match each police reporting district to the corresponding census tract. Not all reporting districts are congruent with census tracts and a share of reporting districts consists of more than one tract. If this is the case, we use a weighted average proportional to the share of the total area occupied by each census tract. We use data from the ACS 2015 5-year estimate on a variety of socioeconomic, demographic, and building indicators. These 5-year estimates take into account data collected at different time points within the survey period. We assume that during our study period from 2010-2017, neighborhood characteristics measured at the beginning of our sample persist in time in such a manner that it does not cause concern for our estimates.

We collect vehicle traffic data to measure general city activity. We use freeway traffic measures from the California Department of Transportation. The California Department of Transportation maintains traffic detectors along freeways to measure flow and speed as part of the Performance Measurement System (PeMS). We download daily traffic volume data for more than 4,000 detectors within Los Angeles County. We aggregate daily traffic counts within the study area for all detectors that have non-missing observations for the entire time series of our study. These data allow us to proxy for economic activity on a daily basis in the city by the number of freeway trips taken on each day.

3.2 Summary Statistics

3.2.1 Crime Dynamics in the City of Los Angeles

Table 1 reports the mean and standard deviation as well as minimum and maximum values of the data along with the sample size. Our unit of analysis is a police reporting district. Panel A shows statistics for different incidence cases at the daily level per reporting district. 65% of all reporting district-day observations do not file a crime report. On average, a reporting district experiences roughly one crime evidence every other day. However, there is considerable variation between the geographical units and some reporting districts see significantly higher average crime levels. For example, 28% of all reports are filed in the reporting districts in the top 10% in terms of crime activity.

Roughly one third of all crime reports fall into the violent crime category and the remaining two thirds are property crimes. There were 443,232 violent crimes between 2010 and 2017, including 2,257 counts of criminal homicides. The occurrence of domestic crimes is lower. Panel C reports the government response measures in our data.

3.2.2 Climate and Neighborhood Dynamics

Panel B summarizes our measures of the city climate. The overall daily maximum temperature reported at Los Angeles area weather stations is relatively high at 76.34 degrees Fahrenheit with a low daily variation due to the rather stable Southern California climate. The temperature range is between 45 and 114 degrees and unlike other studies, our sample does not include days of very cold weather below freezing. The maximum temperature exceeds 85 degrees on roughly every fifth day. The trend in maximum temperatures is increasing over our sample period. This is driven by two facts. At first, there is an increase in the minimum daily maximum temperature and extremely cold days become fewer. Secondly, there is a stark increase in the number of very hot days.

Los Angeles receives very little rainfall. The average daily rainfall is 0.003 inches, but the majority of this rain falls on a few days throughout the year with maximum rainfall of 0.03 inches. The daily mean PM2.5 concentration for EPA pollution monitors in our sample is 11.92 μg/m^3.

Panel D describes neighborhood socioeconomic characteristics for poverty and housing age. Most notable from these demographic statistics is the large within city variation. The mean poverty rate per reporting district is 16%, but varies over the full range from 0 to 100 percent of all surveyed households. The range of our housing stock measure has a similarly large range. While some reporting districts only consist of post WWII housing, some have more than 92% of their housing stock built before 1949.

4 Empirical Setup and Data Manipulation

4.1 Research Design

Our basic research design is based on exploiting both temporal and spatial variation in temperature to estimate heat-crime gradients, i.e. the reduced form impact of higher temperature on crime. To do so, we compare daily rates of criminal activity depending on prevailing temperatures while conditioning out confounding factors of crime.

To explore the temperature-crime relationship, we model the daily number of crimes $crime_{i,t}$ committed in reporting district i at time t using a fixed-effects OLS regression

$$crime_{i,t} = \alpha_{RD} + \beta \; temperature_{i,t} + x_t + \epsilon_{i,t} \tag{1}$$

where $temperature_{i,t}$ are different measures of temperature as discussed below and α_{RD} are police reporting district fixed effects. The vector x_t controls for confounders of crime such as other climatic variables and time fixed effects. Our parameter of interest is β, the marginal effect of an increase in temperature on the number of crimes per neighborhood. Our panel unit of observation is a reporting district-day. The fine spatial disaggregation allows us to analyze whether this relationship depends on the built-up environment and neighborhood characteristics without having to rely on extensive geographic aggregation.

Our identification is based on the assumption that conditional on controls, temperature is as good as random. We bolster this assumption by controlling for a variety of confounders of crime. At first, the inclusion of reporting district fixed effects controls for long-term sorting of criminal activity into neighborhoods of different temperature and assures that we only use time variation of climatic factors to estimate the causal effect of heat.

Next, we control for other climate-related measures such as the amount of precipitation and air pollution. As shown by Herrnstadt et al. (2016), air pollution has an independent effect on crime in Los Angeles. We use the interpolated daily PM2.5 concentration from 15 EPA air pollution monitors within the Los Angeles Metropolitan area. We further control for a variety of time fixed effects. At first, we include day-of-month fixed effects to absorb patterns of crime that are related to calendar effects, such as pay-day effects (Hastings and Washington, 2010; Foley, 2011) on the first and 15th day of each month, or potential misreporting of the crime data to the first of each month. We further control for day-of-week fixed effects to account for within-week patterns of crime. While calendar effects should in principle be unrelated to weather patterns, they might not be orthogonal in our sample and inclusion of these fixed effects can improve the precision of our estimates. We also control for whether any given day overlaps with the local public schools' vacation schedule. Jacob and Lefgren (2003) have shown that there is a significant relationship between criminal activity and school days. Summer vacations and high heat are correlated. We therefore control for a summer vacation dummy that is equal to one whenever schools in the Los Angeles Unified School District are not in session. Finally, we control for the total amount of vehicles on freeways within the study area to account for general city activity.

4.2 Parametrization of Temperature

We next discuss the functional parametrization of the heat-crime gradient. We specify the heat-crime relationship in different ways to allow for a differential effect of extreme heat. In a first step, we use a linear specification of the temperature-crime gradient in degrees Fahrenheit. In specific, we use the daily maximum temperature that occurred on day t. This specification will recover the marginal effect of a unit increase in maximum temperature on crime. In a further specification, we explore the effect of very high temperatures on crime and opt for a binary measure indicating extreme heat. We choose a threshold of 85 or more degrees Fahrenheit. Previous research has documented the various effects of extreme heat on human behavior around that cut-off value (Zhang et al., 2011).

In addition to the linear specification, we follow the literature (Ranson, 2014; Baylis, 2015) and estimate equation 1 with semi-parametric temperature bins of different size. This specification avoids putting restrictive assumptions of linearity on the effect of temperature and allows us to trace out the shape of temperature-crime relationship. We divide the temperature range in bins of 10, 5, and 1 degrees Fahrenheit.

We next need to parametrize temperature over space. This creates both a measurement error issue and a conceptual issue. First, when specifying how we model temperature, we face a measurement problem because we do not observe temperature or pollution data by the same unit of analysis as we only observe data from several weather stations dispersed in our study area. There are significant differences in temperatures within the city resulting from the variation in elevation and distance to the coast of Los Angeles neighborhoods. Second, we do not observe individuals' exposure to heat over the course of their day. People travel within the city for work and leisure, and get exposed to different temperatures at different places. While prevalent heat at their homes might be the largest driver of aggression, heat exposure while commuting or other outdoor activities might also influence criminal behavior contemporaneously or with a lagged effect.

We employ several temperature interpolation methods to show robustness of our results to different parametrization of temperature over space. We start with a nearest neighbor matching type algorithm where we assign to each reporting district the temperature reading from the nearest weather station (as measured by straight line distance between the location of the weather station and the centroid of the police reporting district). This means that neighborhood temperature is taken from the most relevant weather stations, but this leads to potentially sharp discontinuities between spatially close neighborhoods if their border is equidistant to two weather stations. We thus experiment with more detailed interpolation methods and employ inverse distance weighting (IDW) in the appendix.

5 Empirical Results

This section presents the empirical results between heat and crime and explores mechanisms that drive the relationship.

5.1 Results for the Temperature-Crime Relationship

We first report regression results for the heat-crime relationship and then discuss estimates for the interaction models. Table 2 reports coefficient estimates and standard errors of our model parameters based on estimating equation (1). We find a positive and statistically significant parameter estimate for β_1 in all specifications. In the linear temperature specifications in columns (1)-(3), we start by estimating the model using daily maximum temperature only, and then subsequently add more controls. In the simplest specification, we find an average increase in crime of 0.12% (=.000627/.502) for each degree higher maximum daily temperature. The results change only marginally if we control for additional time fixed effects in column 2 or other climatic confounders of crime such as air pollution and precipitation (column 3).

In column (4) we report results for the specification with the extreme heat threshold variable (temperature above 85 degrees Fahrenheit). Again, the coefficient is statistically significant and positive. We estimate an increase in crime of 2.21% (=0.0111/0.532) on days that are hotter than 85 degrees compared to comparable days below that threshold. We next use a semi-parametric bin estimator. In column (5), we include the 10-degrees Fahrenheit bins defined above and treat the 65-75 degree bin as the omitted category. This temperature range is perceived by many people as most comfortable and will act as our baseline (Albouy et al., 2016). We find statistically significant results for the bins above this threshold. The coefficients increase with temperature until the maximum temperature reaches 95 degrees. Above these temperatures crime slightly dips. At very high temperatures above 105F, the estimated coefficient becomes negative (compared to the omitted category of 65-75F). This suggests that criminal activity increases when temperatures rise above comfortable levels and then sharply decline if it gets extremely hot. This means that the effect of heat on crime is not monotonic, but has an inverted "hockey stick" shape. Thus, fitting a simple linear model exaggerates the impact of crime at very high temperatures. However, the number of observations for this very high temperature bin is small and the coefficient is measured with sizable error.

In every specification we find that air pollution has a statistically significant positive effect on crime regardless of temperature. This is consistent with earlier studies that have found sizable effects of PM2.5 concentration on a variety of human behavior consistent with evidence in Graff Zivin and Neidell (2013), Chang et al. (2019), and Herrnstadt et al. (2016). Similarly, we find a robust negative relationship between rain and crime and conclude that rainfall deters criminal activity in Los Angeles.

We next make the model even more non-parametric and estimate the effect of temperature using 5 and 1-degree temperature bins. Figure 2 depicts the marginal effect of each temperature bin relative to the baseline temperature of 65 degrees Fahrenheit. This most flexible model confirms the results of the 10-degrees bin estimator. The marginal effect of heat on crime appears to be positive for the majority of the temperature range until it declines again at very high temperatures around 105 degrees Fahrenheit.

To put these effects into comparison, the estimates suggest that a one standard deviation increase in daily maximum temperature of 10 degrees Fahrenheit (= 5.55 degrees Celsius) leads on average to an increase of about 1.2% more crime counts per neighborhoods. Multiplying this effect with the number of police reporting districts and the number of days per year, this is equivalent to an increase of 3,700 more crimes per year.

5.2 How Does Urban Poverty Affect the Heat-Crime Relationship?

We now focus on distributional impacts and the question how the effect of heat on crime varies over space and neighborhood characteristics. We are particularly interested in the interaction of the effect with poverty. If the costs of extreme weather events through the heat crime channel are unequally distributed, this will increase the inequality of quality of life within the city. In this section, we test for how the heat-crime relationship varies with neighborhood income. To do so, we estimate the following interaction regression:

$$crime_{i,t} = \alpha_{RD} + \beta_1 \ temperature_{i,t} + \beta_2 \ temperature_{i,t} \times poverty_i + \epsilon_{i,t} \tag{2}$$

where $poverty_i$ denotes the poverty level of reporting district i. We measure poverty by the share of families in a census tract that live below the poverty line. The parameter of interest is β_2, the differential effect of weather on crime by different poverty levels. A positive and statistically significant effect would indicate that the burden of the heat-crime relationship is unequally distributed toward the poor that already suffer from lower quality of life.

In Table 3, we report regression results for different specifications of the interaction of heat and poverty. In columns (1) and (2), we interact the daily maximum temperature variable with both a linear measure of neighborhood poverty as well as with an indicator measuring being above the median neighborhood poverty level. Both interaction terms are positive and statistically significant. The noisy point estimate of β_1 in column (1) suggests that for neighborhoods with zero poverty, the effect of heat on crime is actually negative. To quantify the heterogeneity of the effect, we use the model to calculate marginal effects at the 25th and 75th percentile of the poverty. The richest 25% of the reporting districts of the City of Los Angeles have poverty levels of less than 5.06%. At this threshold, the marginal effect of a one degree increase in temperature is close to zero at 0.003%. The 75th percentile is given by poverty rates of 23.99% where the marginal effect of an equally large temperature increase on crime is 0.17%. The heat-crime gradient is therefore almost 50 times as large between the 25th and 75th percentile of the poverty distribution.

In columns (2), we look at a slightly different interactions with the poverty measure and interact the temperature measure with an indicator whether a neighborhood is above or below the median of the poverty distribution. Again we find a positive and precisely estimated interaction term. On average, the effect is not statistically significant for the neighborhoods below the median poverty level. We confirm these patterns using regressions stratified by income. Figure 3 presents the coefficient estimates of separate regressions for each neighborhood poverty decile. The results indicate that the effect of heat on crime is concentrated in neighborhoods in the upper quintile of the poverty distribution, while the effect is quite muted for the rest of the neighborhoods. For two of the lower 30% of the poverty distribution, the estimated effect is even negative albeit statistically significant. Overall the results show that the effect of heat on crime is concentrated in the poorest neighborhoods with very little effect on neighborhoods with less severe poverty. This indicates that the costs of extreme weather-induced crime is unequally distributed toward the poor. Since these neighborhoods already suffer from high poverty and crime, weather shocks make the city more unequal.

5.3 An Adaptation Mechanism

We next focus on the question why the effect of heat on crime is so much stronger in poorer neighborhoods. We posit the theory that this is driven by a lack of adaptation. On a larger geographical scale, the climate change literature has documented that poorer countries are less able to adapt to climate change-induced weather events and thus suffer more from its adverse events (Mendelsohn et al., 2006; Dell et al., 2012). In this section, we explore whether this mechanism also holds within the city and varies by human geography over small distances. In our context, the most plausible adaptation technology to combat extreme heat is the usage of air conditioning. In an ideal experiment, we would observe data on air conditioning availability and usage, and interact these measures with the heat-crime gradient.

Unfortunately, detailed data on whether neighborhoods are equipped with air-conditioning is not available to us. Instead, we focus on neighborhood indicators that we believe are correlated with air conditioning, namely the age of the housing stock. The age of the housing stock matters because older housing units are even less likely to have been built with air conditioning. In addition, retrofitting and installing air conditioning in older buildings is more expensive due to differences in housing design. Air conditioning did not become common in the United States until the late 1940s and early 1950s with the invention of economical window AC units. The American Housing Survey estimates that only 33% of all housing units built before 1940 were equipped with central air while this number increased to 88% in recent years. The census reports the number of housing units by decade of construction by neighborhood. We measure housing age by the share of houses that were built before 1949 and use this variable as a proxy for the cost of installing and operating air conditioning.[6]

[6]One disadvantage of this approach is the possible correlation with lead exposure with housing age as childhood lead exposure is thought to be a main determinant of crime (Nevin, 2007; Reyes, 2007). Park et al. (2018) find higher blood exposure to lead for children living in older residences. However, this would only create a problem if lead exposure interacts with heat as the reporting district fixed effects absorb the level

We repeat the interaction analysis by including interaction terms with the housing age variable. The effect is confounded by the fact that poorer people will have a lower probability of living in a housing unit with air conditioning (Davis and Gertler, 2015). Indeed, in our sample the share of poverty is positively correlated with the share of old housing, indicating that poorer households live in older neighborhoods. However, the correlation coefficient is only 0.278 and there is a large share of older neighborhoods with low poverty and vice versa. Columns (3) and (4) of Table 3 reports the regression results for the interaction term with housing age. We see positive interaction terms for both models indicating that the effect of heat on crime is stronger in older neighborhoods. These interaction terms persist if we separately include interaction terms for poverty in column (5). Both interaction terms are positive and significant, indicating that poverty and housing age have an independent effect on adaptation to extreme heat. Our results suggest that human geography plays a large role in mitigating the negative effects of extreme heat on crime. Both richer and newer neighborhoods show more resilience to dealing with high heat and its effect on crime.

5.4 Disaggregating by Crime Categories

After establishing the reduced-form effect of heat on crime, we are interested in the mechanisms that drive this relationship. To test the mechanisms of the heat-crime relationship, we categorize crimes into different categories depending on type, location, and victim of the crime. At first, we distinguish crime reports by their severity by creating counts of violent crimes and non-violent property crimes. In the former category, we include murder, assault, robbery, battery, rape, arson, and kidnapping as outlined in Appendix B.[7] The latter category consists of crimes such as theft, fraud, and burglary as they relate to others' property.

We further distinguish domestic crimes. We classify crimes as domestic if they take place in residences. We then look at crimes that were classified as assaults or abuses of intimate partners and children. These are incidents where the victim was known by the perpetrator. We posit that this kind of crime is less responsive to police deterrence. Lastly, we look at crimes committed against homeless people. In general, domestic crimes and crimes against intimate partners and homeless persons have very little monetary reward. For example, the

effect of lead. If the interaction is important, we treat it as another channel through which temperature can increase crime.

[7]By examining violent crimes, we also check for underreporting on very hot or cold days that could drive the results in the previous subsection. Violent crimes such as aggravated assault are more likely to be reported regardless of the prevailing temperature.

monetary benefit of domestic violence against family members should be close to zero and would better be interpreted as a crime of passion. The rational criminal model of Section 2 would not suggest effects on these types of crime if the heat-crime channel is driven by differences in the utility of crimes. Instead, it would predict an increase in non-violent property crimes.

In Table 4 we report regression results for various crime measures from the extreme heat specification. We find statistically significant effects of temperature on violent crimes. These effects are larger than for overall crime incidents. The regression estimates imply that on hot days with temperatures above 85F, there are 5.72% (=.00892/.156) more reported violent crime incidents. We find similarly positive and statistically significant effects for domestic crimes and crimes against intimate partners. In each specification, the model parameters indicate that these crimes increase on hotter days. We also find a positive effect on crimes against homeless for a shorter time series. In contrast, we do not find a significant relationship between non-violent crimes and heat, and the negative point estimate suggests that property crimes decrease on hot days.

Our findings suggest that heat only affects violent crimes and that the results for the overall crime response to temperature changes is driven by this category. This sheds light on the question whether heat decreases opportunity costs of crime or whether it effects decision-making directly. If higher ambient temperatures decreased the opportunity costs of crimes, we would expect a similar result for property crimes as those crimes face the same trade-off as violent crimes. We hypothesize that violent crimes have less of a financial motive. Finding the strongest results in this category therefore suggests that the aggression channel is very strong. We conclude that the empirical evidence supports the theory that heat reduces mental capacity and self-control. However, we cannot rule out that heat increases the direct costs of violent and non-violent crimes differentially.

6 Evaluating the Government Response to High Heat

We now turn our attention to the response of city administration towards crime due to extreme heat. Police departments have a large amount of discretion about investigating calls for service and enforcing violations of the law while on patrol. This discretion can occur either at the command level or from the actions of an individual police officer. Extreme heat raises the cost of policing enforcement as it mainly takes place outdoors. We investigate whether the Los Angeles Police Department devotes less effort on hot days on investigating crimes and apprehending suspects. Such a supply side response to unpleasant working conditions might partly explain why crime is higher on hot days. There is recent evidence that government quality is responsive to climate. Obradovich et al. (2018) have shown that adverse weather conditions lead to fewer food safety inspections and police stops.

The analysis is based on a database of internal police communication between police officers and the LAPD dispatcher that allows us to create certain measures of policing effort. We begin by examining the LAPD calls for service and focus on *Code 6* to see whether police investigations increase on hot days. *Code 6* is the code used when a police officer arrives on-site and leaves their patrol car to investigate an issue. We interpret this as both a measure of effort and of the presence of the police force, and thus a proxy of police deterrence.

We then look at arrest counts. Arrests can be interpreted as a measure of success of policing effort in response to an increase in crime on hot days. Lastly, we focus on traffic stop data to evaluate the effort the police force. Vehicle stops are a less costly form of police intervention to deter unlawful activity on the road. In this regression, we control for the amount of traffic on Los Angeles streets to make sure that this potential change in traffic stops on hot days is not due to an increase or decrease of the amount of cars on the road.

Table 5 reports the regression results testing for a relationship between heat and these measures of government effort. We observe a statistically insignificant decrease in *Code 6* investigations during hot days. On days with maximum temperature above 85 degrees Fahrenheit, we observe 1.1% (=-0.00321/0.273) fewer police investigations following officers leaving their vehicle. We estimate a small positive effect of heat on the number of arrests, yet this coefficient is estimated with large standard errors and not statistically different from zero. Lastly, we find a large negative effect for vehicle traffic stops. On hot days above 85 degrees, police officers are pulling over 6.6% fewer cars than they do on the average day whose temperature is below that threshold. Together with the negative effects for precipitation, we interpret this as a reduction in government effort on days featuring worse weather. This suggests that part of the reduced form effect of heat on crime found earlier in this paper is driven by a lack of deterrence.

7 Conclusion

In May 2019, the global carbon dioxide concentration now stands at 415 parts per million and may rise closer to 500 over the next few decades. Climate scientists are in agreement that this trend portends a sharp increase in the count of extremely hot days. Given the expectation of increased heat, an active research agenda in climate change economics has focused on measuring the consequences of rising temperatures.

The quality of life of poor people is likely to be most severely affected by climate change. Richer people have access to more coping strategies. Given that most people live in cities and that poor people tend to live in poor areas within cities, climate change is likely to increase within city quality of life inequality. Our paper's new estimates are helpful in quantifying the possible magnitude of these effects.

This paper explores the relationship between heat and crime and its interaction with the built-up environment within the city. We have studied how quality of life within the city of Los Angeles changes as a function of extreme heat. We find that the marginal effect of higher temperatures on violent behavior is larger in neighborhoods that are poorer and have older housing stock. We document that heat only affects violent crimes while property crimes are not affected by higher temperatures. We find the strongest effects in crimes committed at home and against victims the perpetrator is familiar with. This leads us to conclude that the quality of living quarters matters and that poorer residents are the least likely to be able to cope with higher heat.

Past research has documented that climate change's impact varies drastically between and within countries. For example, Deryugina and Hsiang (2014) show a strong correlation between county-wide productivity and heat. Using these units of analysis, this research has not examined the urban implications of climate change adaptation because these data offer little opportunity to study within-city variation in coping with extreme climate events. We show that this inequality is pronounced over very small distances within the same city. These results have important implications for climate justice and provide an economic rationale for subsidizing climate change-mitigating investments such as air conditioning for poorer households. The diffusion of air conditioning has reduced high heat mortality (Barreca et al., 2016) over the course of the 20th century. We conjecture that investments into air conditioning will also attenuate the heat-crime gradient.

Certain measures of police activity decrease in response to heat. While such a shift of policing effort away from minor infractions towards more serious crime might be socially optimal conditional on fixed resources, it might not be so if police resources are flexible in the medium run and calls for more efficient management in response to climate shocks. Our findings on how urban policing evolves on hot and polluted days suggests that the rise of *Big Data* will allow for new insights about measuring governance effort. Such analysis encourages accountability by identifying weak spots in service coverage on stressful days. Given that we find that the Los Angeles Police Department exerts less effort on extremely hot days, the city's leadership can offer incentives or add more patrol cars on such days to supplement the supply of government services.

References

Ailshire, Jennifer A and Eileen M Crimmins, "Fine particulate matter air pollution and cognitive function among older US adults," *American Journal of Epidemiology*, 2014, *180* (4), 359–366.

Albouy, David, Walter Graf, Ryan Kellogg, and Hendrik Wolff, "Climate Amenities, Climate Change, and American Quality of Life," *Journal of the Association of Environmental and Resource Economists*, 2016, *3* (1), 205–246.

Almås, Ingvild, Maximilian Auffhammer, Tessa Bold, Ian Bolliger, Aluma Dembo, Solomon M Hsiang, Shuhei Kitamura, Edward Miguel, and Robert Pickmans, "Destructive Behavior, Judgment, and Economic Decision-making under Thermal Stress," Technical Report, National Bureau of Economic Research 2019.

Anderson, Craig A, "Heat and violence," *Current Directions in Psychological Science*, 2001, *10* (1), 33–38.

Anderson, Craig A., Kathryn B. Anderson, Nancy Dorr, Kristina M. DeNeve, and Mindy Flanagan, "Temperature and aggression," 2000, *32*, 63 – 133.

Baron, Robert A and Paul A Bell, "Aggression and heat: The influence of ambient temperature, negative affect, and a cooling drink on physical aggression.," *Journal of Personality and Social Psychology*, 1976, *33* (3), 245.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro, "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century," *Journal of Political Economy*, 2016, *124* (1), 105–159.

Baylis, Patrick, "Temperature and temperament: Evidence from a billion tweets," *Energy Institute Working Paper*, 2015.

Becker, Gary S, "Crime and punishment: An economic approach," in "The Economic Dimensions of Crime," Springer, 1968, pp. 13–68.

Boyanowsky, Ehor, "Violence and aggression in the heat of passion and in cold blood: The Ecs-TC syndrome," *International Journal of Law and Psychiatry*, 1999, *22* (3-4), 257–271.

Bruederle, Anna, Jörg Peters, and Gareth Roberts, "Weather and crime in South Africa," Technical Report, Ruhr Economic Papers 2017.

Burke, Marshall B, Edward Miguel, Shanker Satyanath, John A Dykema, and David B Lobell, "Warming increases the risk of civil war in Africa," *Proceedings of the National Academy of Sciences*, 2009, *106* (49), 20670–20674.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, "Climate and conflict," *Annual Review of Economics*, 2015, *7* (1), 577–617.

Chang, Tom Y, Joshua Graff Zivin, Tal Gross, and Matthew Neidell, "The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China," *American Economic Journal: Applied Economics*, 2019, *11* (1), 151–72.

Chay, Kenneth Y and Michael Greenstone, "The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession," *The Quarterly Journal of Economics*, 2003, *118* (3), 1121–1167.

Chen, Jiu-Chiuan and Joel Schwartz, "Neurobehavioral effects of ambient air pollution on cognitive performance in US adults," *Neurotoxicology*, 2009, *30* (2), 231–239.

Currie, Janet, Matthew Neidell, and Johannes F Schmieder, "Air pollution and infant health: Lessons from New Jersey," *Journal of Health Economics*, 2009, *28* (3), 688–703.

Davis, Lucas W and Paul J Gertler, "Contribution of air conditioning adoption to future energy use under global warming," *Proceedings of the National Academy of Sciences*, 2015, *112* (19), 5962–5967.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

Deryugina, Tatyana and Solomon M Hsiang, "Does the environment still matter? Daily temperature and income in the United States," Technical Report, National Bureau of Economic Research 2014.

DiPasquale, Denise and Matthew E Kahn, "Measuring neighborhood investments: An examination of community choice," *Real Estate Economics*, 1999, *27* (3), 389–424.

Foley, C Fritz, "Welfare payments and crime," *The Review of Economics and Statistics*, 2011, *93* (1), 97–112.

Galster, George and Patrick Sharkey, "Spatial foundations of inequality: A conceptual model and empirical overview," *RSF*, 2017.

Goodman, Joshua, Michael Hurwitz, Jisung Park, and Jonathan Smith, "Heat and Learning," Technical Report, National Bureau of Economic Research 2018.

Gyourko, Joseph and Joseph Tracy, "The structure of local public finance and the quality of life," *Journal of Political Economy*, 1991, *99* (4), 774–806.

Harries, Keith D, Stephen J Stadler, and R Todd Zdorkowski, "Seasonality and assault: Explorations in inter-neighborhood variation, Dallas 1980," *Annals of the Association of American Geographers*, 1984, *74* (4), 590–604.

Hastings, Justine and Ebonya Washington, "The first of the month effect: consumer behavior and store responses," *American Economic Journal: Economic Policy*, 2010, *2* (2), 142–62.

Heaton, Paul, *Hidden in plain sight*, RAND Corporation, 2010.

Heller, Sara B, Anuj K Shah, Jonathan Guryan, Jens Ludwig, Sendhil Mullainathan, and Harold A Pollack, "Thinking, fast and slow? Some field experiments to reduce crime and dropout in Chicago," *The Quarterly Journal of Economics*, 2017, *132* (1), 1–54.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian, "Air pollution as a cause of violent crime: Evidence from Los Angeles and Chicago," Technical Report, Technical Report, mimeo 2016.

Heyes, Anthony and Soodeh Saberian, "Temperature and decisions: evidence from 207,000 court cases," *American Economic Journal: Applied Economics*, 2018.

Hsiang, Solomon M, Marshall Burke, and Edward Miguel, "Quantifying the influence of climate on human conflict," *Science*, 2013, *341* (6151), 1235367.

Huynen, MMTE-Martens, Pim Martens, Dieneke Schram, Matty P Weijenberg, and Anton E Kunst, "The impact of heat waves and cold spells on mortality rates in the Dutch population.," *Environmental Health Perspectives*, 2001, *109* (5), 463.

Jacob, Brian A and Lars Lefgren, "Are idle hands the devil's workshop? Incapacitation, concentration, and juvenile crime," *American Economic Review*, 2003, *93* (5), 1560–1577.

Jacob, Brian, Lars Lefgren, and Enrico Moretti, "The dynamics of criminal behavior evidence from weather shocks," *Journal of Human resources*, 2007, *42* (3), 489–527.

Kahn, Matthew E and Pei Li, "The Effect of Pollution and Heat on High Skill Public Sector Worker Productivity in China," Technical Report, National Bureau of Economic Research 2019.

Kposowa, Augustine J and Kevin D Breault, "Reassessing the structural covariates of US homicide rates: A county level study," *Sociological Focus*, 1993, *26* (1), 27–46.

Laibson, David, "A cue-theory of consumption," *The Quarterly Journal of Economics*, 2001, *116* (1), 81–119.

Levitt, Steven D, "Using electoral cycles in police hiring to estimate the effect of police on crime," *American Economic Review*, 1997, *87* (3), 270.

_ , "Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not," *Journal of Economic Perspectives*, 2004, *18* (1), 163–190.

Massey, Douglas S and Nancy A Denton, *American apartheid: Segregation and the making of the underclass*, Harvard University Press, 1993.

Mendelsohn, Robert, Ariel Dinar, and Larry Williams, "The distributional impact of climate change on rich and poor countries," *Environment and Development Economics*, 2006, *11* (2), 159–178.

Nakicenovic, Nebojsa, Joseph Alcamo, A Grubler, K Riahi, RA Roehrl, H-H Rogner, and N Victor, *Special report on emissions scenarios (SRES), a special report of Working Group III of the intergovernmental panel on climate change*, Cambridge University Press, 2000.

Nevin, Rick, "Understanding international crime trends: the legacy of preschool lead exposure," *Environmental Research*, 2007, *104* (3), 315–336.

Nilsson, Anders and Felipe Estrada, "The inequality of victimization: trends in exposure to crime among rich and poor," *European Journal of Criminology*, 2006, *3* (4), 387–412.

Obradovich, Nick, Dustin Tingley, and Iyad Rahwan, "Effects of environmental stressors on daily governance," *Proceedings of the National Academy of Sciences*, 2018, p. 201803765.

O'Flaherty, Brendan and Rajiv Sethi, "The racial geography of street vice," *Journal of Urban Economics*, 2010, *67* (3), 270–286.

Park, Jisung, Mook Bangalore, Stephane Hallegatte, and Evan Sandhoefner, "Households and heat stress: estimating the distributional consequences of climate change," *Environment and Development Economics*, 2018, *23* (3), 349368.

Ranson, Matthew, "Crime, weather, and climate change," *Journal of Environmental Economics and Management*, 2014, *67* (3), 274–302.

Reyes, Jessica Wolpaw, "Environmental policy as social policy? The impact of childhood lead exposure on crime," *The BE Journal of Economic Analysis & Policy*, 2007, *7* (1).

Rotton, James and James Frey, "Air pollution, weather, and violent crimes: Concomitant time-series analysis of archival data.," *Journal of Personality and Social Psychology*, 1985, *49* (5), 1207.

Sampson, Robert J, "Crime in cities: The effects of formal and informal social control," *Crime and Justice*, 1986, *8*, 271–311.

Vrij, Aldert, Jaap Van der Steen, and Leendert Koppelaar, "Aggression of police officers as a function of temperature: An experiment with the fire arms training system," *Journal of Community & Applied Social Psychology*, 1994, *4* (5), 365–370.

Zhang, Hui, Edward Arens, and Wilmer Pasut, "Air temperature thresholds for indoor comfort and perceived air quality," *Building Research & Information*, 2011, *39* (2), 134–144.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang, "Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants," *Journal of Environmental Economics and Management*, 2018, *88*, 1–17.

Zivin, Joshua Graff and Matthew Neidell, "Environment, health, and human capital," *Journal of Economic Literature*, 2013, *51* (3), 689–730.

Table 1: Summary Statistics (2010-2017)

Panel A: Crime Incidents at Reporting District-Day

	Mean	Std Dev	Min	Max	N
All Crimes	.501	.847	0	61	3,307,704
Violent crimes	.134	.424	0	19	3,307,704
Property crimes	.310	.627	0	61	3,307,704
Domestic crimes	.172	.460	0	21	3,307,704
Crimes against intimate partners	.030	.179	0	4	3,307,704
Crimes against homeless persons	.010	.105	0	4	264,255

Panel B: Weather Data by Day

	Mean	Std Dev	Min	Max	N
Max daily temperature	76.34	10.36	45	114	3,296,105
Daily max temperature $\geq$ 85F	.215	.411	0	1	3,307,704
Precipication	.031	.182	0	7	3,296,081
Daily mean PM2.5 concentration	11.92	6.41	0	85.4	2,108,865

Panel C: Police Response Indicators at Reporting District-Day

	Mean	Std Dev	Min	Max	N
Officer Investigations (Code 6)	.246	.671	0	49	3,576,528
Arrests	.282	.945	0	199	4,085,100
Vehicle Stops	1.24	6.27	0	7962	3,774,669

Panel D: Reporting District Demographics

	Mean	Std Dev	Min	Max	N
Share of Families below Poverty Line	.160	0.135	0	1	1,116
Share of Housing Built before 1949	.337	.233	0	.928	1,118

Table 2: Measuring the overall effect of weather and pollution on Los Angeles crime

	(1)	(2)	(3)	(4)	(5)
Max daily temperature	0.000627***	0.000555***	0.000617***		
	(0.000194)	(0.000129)	(0.000191)		
Daily max $\geq$ 85F				0.0111***	
				(0.00222)	
Temperature 45-55F					-0.0221
					(0.0138)
Temperature 55-65F					-0.00378
					(0.00614)
Temperature 65-75F					omitted category
Temperature 75-85F					0.00517*
					(0.00288)
Temperature 85-95F					0.0151***
					(0.00320)
Temperature 95-105F					0.0137***
					(0.00461)
Temperature 105-115F					-0.0129
					(0.0143)
Precipitation			-0.0147***	-0.0187***	-0.0146***
			(0.00505)	(0.00520)	(0.00476)
PM2.5 concentration			0.000948***	0.000989***	0.000964***
			(0.000360)	(0.000354)	(0.000369)
Traffic flow			-0.000316	-0.000207	-0.000275
			(0.00170)	(0.00170)	(0.00170)
Linear time trend	No	Yes	Yes	Yes	Yes
Day of month FE	No	Yes	Yes	Yes	Yes
Day of week FE	No	Yes	Yes	Yes	Yes
Summer vacation FE	No	Yes	Yes	Yes	Yes
Sample mean	0.502	0.502	0.532	0.532	0.532
Percentage effect	0.12%	0.11%	0.12%	2.21%	n/a
R-squared	0.177	0.181	0.182	0.182	0.182
Observations	3,296,105	3,296,105	2,031,859	2,031,859	2,031,859

Dependent variable: Daily number of crimes by reporting district

All regressions include reporting district and year-month fixed effects

Standard errors clustered at the daily level: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table 3: The role of poverty and older housing in explaining within city variation in the crime and heat gradient

Interaction with	(1) Poverty	(2) Poverty	(3) Housing	(4) Housing	(5) Combined
Max daily temperature	-0.000224	0.0000730	0.000126	0.000190	-0.000458*
	(0.000179)	(0.000167)	(0.000198)	(0.000187)	(0.000191)
Max daily temperature × Share poverty	0.00487***				0.00457***
	(0.000528)				(0.000531)
Max daily temperature × Above median poverty		0.000988***			
		(0.000151)			
Max daily temperature × Share old housing			0.00140***		0.000825**
			(0.000281)		(0.000281)
Max daily temperature × Above median housing age				0.000829***	
				(0.000136)	
Precipitation	-0.0146**	-0.0146**	-0.0145**	-0.0144**	-0.0144**
	(0.00507)	(0.00505)	(0.00506)	(0.00505)	(0.00507)
PM2.5 concentration	0.000945**	0.000941**	0.000946**	0.000936**	0.000940**
	(0.000363)	(0.000361)	(0.000362)	(0.000360)	(0.000363)
Sample Mean	0.535	0.532	0.534	0.532	0.535
R-squared	0.182	0.182	0.182	0.182	0.182
Observations	2,016,442	2,031,859	2,021,632	2,031,859	2,016,442

Dependent variable: Daily number of crimes by reporting district

Standard errors clustered at the daily level: ${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$

Table 4: Measuring the effect of weather and pollution on different types of crime

Type of crime	(1) Violent	(2) Property	(3) Domestic	(4) Intimate	(5) Homeless
Daily max $\geq$ 85F	0.00892***	-0.00104	0.00433***	0.00220***	0.00139**
	(0.00104)	(0.00159)	(0.00153)	(0.000416)	(0.000704)
Precipication	-0.0124***	-0.00152	-0.00300	-0.000208	-0.00158*
	(0.00259)	(0.00359)	(0.00395)	(0.000764)	(0.000810)
PM2.5 concentration	0.000421***	0.000448*	0.000781**	0.0000939***	0.000139**
	(0.000109)	(0.000235)	(0.000311)	(0.0000292)	(0.0000637)
Sample Mean	0.156	0.317	0.181	0.0336	0.0117
Percentage effect	5.72%	-0.33%	2.39%	6.53%	11.8%
R-squared	0.0933	0.124	0.0835	0.0251	0.0394
Observations	2,031,859	2,031,859	2,031,859	2,031,859	181,564

Dependent variable: Daily number of crimes by reporting district

Standard errors clustered at the daily level : ${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$

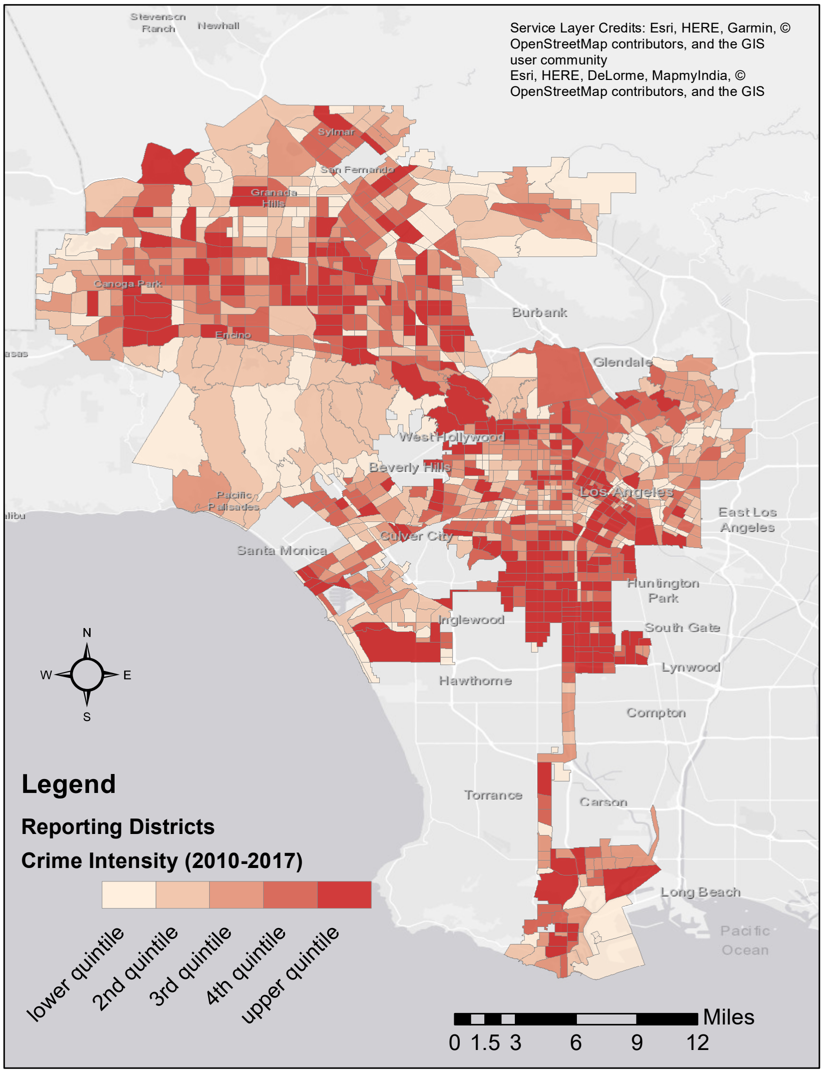
Table 5: Understanding how the police respond as a function of weather and pollution

	(1) Investigations	(2) Arrests	(3) Vehicle stops
Daily max temperature $\geq$ 85F	-0.00321	0.00311	-0.0947***
	(0.00380)	(0.00316)	(0.0188)
Precipitation	-0.0461***	-0.0633***	-0.433***
	(0.00627)	(0.00841)	(0.0481)
PM2.5 concentration	-0.000106	0.000344*	0.00222*
	(0.000245)	(0.000205)	(0.00124)
Traffic flow	0.00482***	0.00709***	0.0337***
	(0.00144)	(0.00131)	(0.00695)
Sample Mean	0.273	0.368	1.469
Percentage effect	-1.1%	0.84%	-6.6%
R-squared	0.156	0.231	0.0358
Observations	2,029,264	2,031,859	2,031,859

Dependent variable: Police effort measures by reporting district

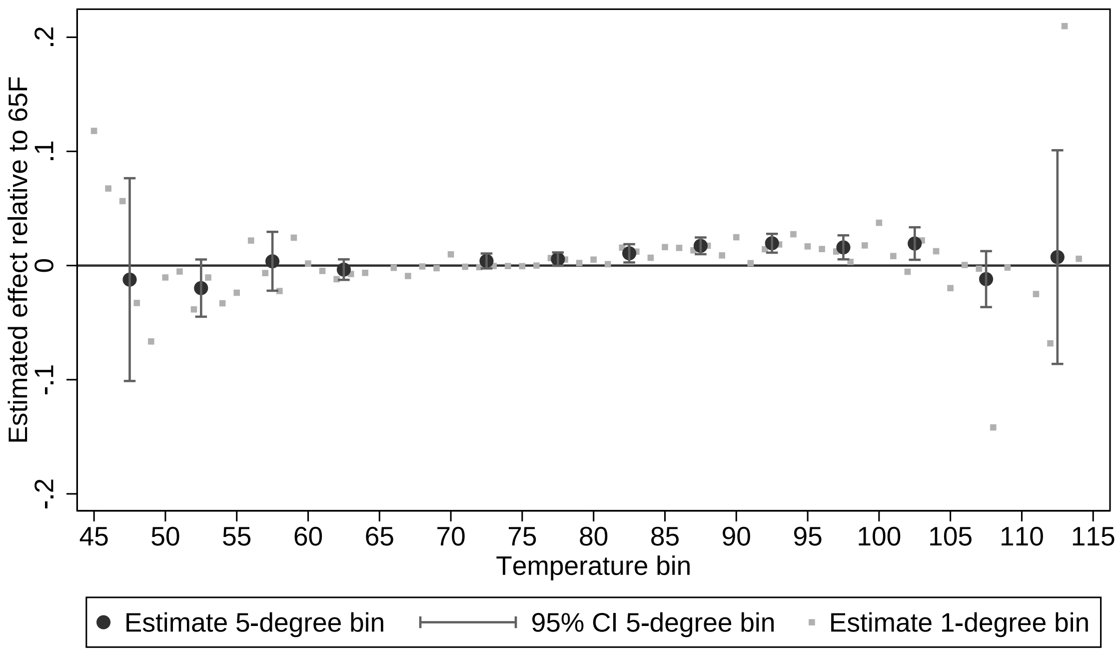
Standard errors clustered at the daily level: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Figure 1: Geography of Study Area



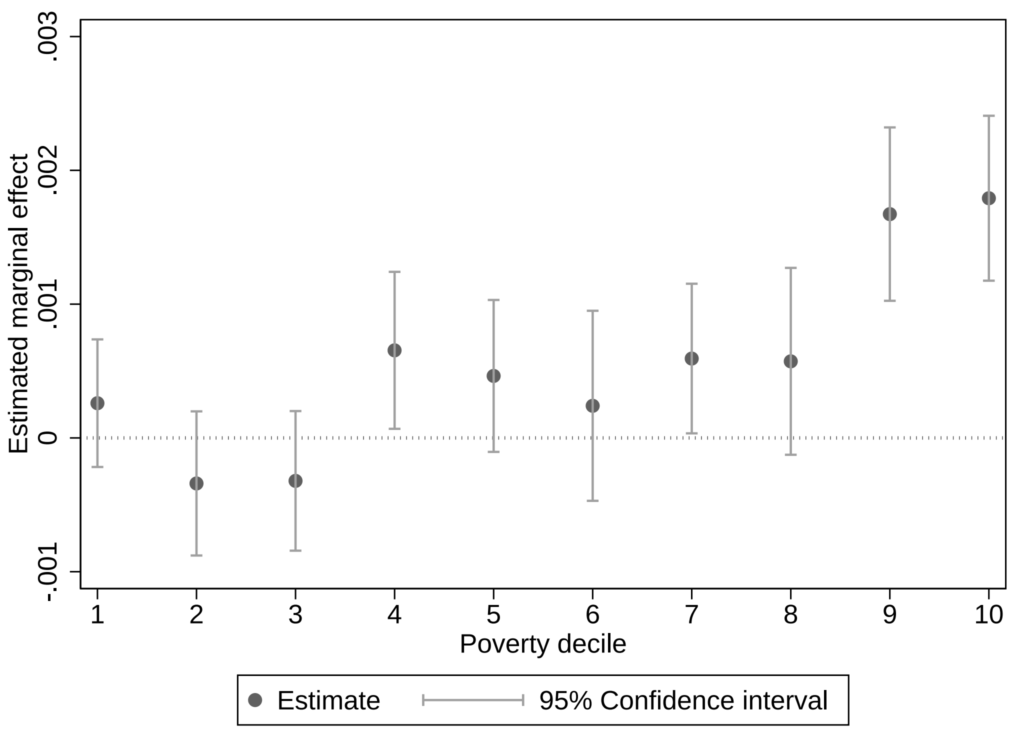
Notes: This figure shows the reporting districts of the Los Angeles Police Department within Greater Los Angeles metropolitan area. Darker shades indicate higher average crime intensity measured by the total number of crime reports over the whole study period of 2010-2017.

Figure 2: Bin estimator results



Notes: This figure plots the point estimates for the 5-degree and 1-degree temperature bin regressions relative to the 65 degrees Fahrenheit omitted category. It also depicts the 95% confidence interval of the 5-degree bin estimates.

Figure 3: Stratified regressions by poverty levels



Notes: This figure plots the point estimates for the marginal effect of a one degree Fahrenheit higher daily maximum temperature on crime reports stratified by police reporting poverty deciles together with the 95% confidence interval. Poverty is measured as the share of families living below the poverty limit and increases from left to right.

A Appendix

A.1 Welfare Calculations

We next quantify the monetary cost of heat-induced crime. We use cost estimates for different crime categories from Heaton (2010) to measure the additional burden of crime on a hot day. We focus on index crimes defined by the Federal Bureau of Investigation (FBI) and include: homicide, rape, robbery, assault, burglary, larceny, and car theft. Table 6 reports regression results for these crime categories with the estimated dollar cost. We multiply this number with the marginal effect size and the number of reporting districts. We calculate a yearly cost in excess of $33 million dollars. This number is mainly driven by increases in assaults ($83 million) and dampened severely by the (statistically not significant) negative effects on homicide.

Table 6: Disaggregated crime regression results

	(1) Homicide	(2) Rape	(3) Robbery	(4) Assault	(5) Burglary	(6) Larceny	(7) Car theft
Daily max $\geq$ 85F	-0.0000171	0.000167	0.000170	0.00233***	-0.00113*	-0.0000295*	-0.000839*
	(0.0000642)	(0.000115)	(0.000349)	(0.000443)	(0.000638)	(0.0000178)	(0.000440)
Precipitation	-0.000244***	0.000198	-0.00219***	-0.00365***	0.00330**	-0.0000509*	0.00299***
	(0.0000860)	(0.000201)	(0.000662)	(0.000727)	(0.00137)	(0.0000286)	(0.000814)
PM2.5 concentration	-8.37e-08	0.0000340***	0.0000128	0.000122***	-0.00000680	-0.00000136	-0.0000385
	(0.00000363)	(0.0000114)	(0.0000193)	(0.0000270)	(0.0000389)	(0.000000909)	(0.0000273)
Sample Mean	0.000834	0.00257	0.0247	0.0291	0.0756	0.0000871	0.0428
Percentage effect	-2.05%	6.49%	7.29%	8.00%	-1.49%	-33.9%	-1.96%
R-squared	0.00156	0.00356	0.0285	0.0237	0.0345	0.00103	0.0235
Observations	2,031,859	2,031,859	2,031,859	2,031,859	2,031,859	2,031,859	2,031,859
Cost estimate (in thousands)	$-61,109	$15,032	$4,725	$83,984	$-6,114	$-26	-$-3,147

Dependent variable: Daily number of crimes by reporting district

Standard errors clustered at the daily level : $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Crime cost estimates are taken from Heaton (2010)

Using estimates from the previous literature on the deterrents of crime, we can also compare the effect of extreme temperature to other measures to combat violent crime. Levitt (1997) estimates an elasticity of violent crime with respect to the deployment of police officers -1. A rough back-on-the-envelope calculation suggests that to offset the effect of a very hot day on crime, LAPD would have to increase the number of police officers by 5.7% or 513 officers out of the total 9,000 officers currently employed by LAPD. To estimate the cost of this deployment, we analyze average wages of police officers from the Sacramento Bee public database of earnings of public employees in California. In 2017, the average police officer in Los Angeles County earned wages (including overtime pay) and benefits of $124,600. The wage cost alone of this extra deployment results in costs in excess of $60 million per year, not including the need for additional equipment for law enforcement officers to perform their duties.

A.2 Net Effects or Displacement

In a next step, we distinguish between net effects and displacement effects which are both consistent with the results of the contemporaneous regression models. In our previous analysis we treated the effects of heat on crime as net increases, such that an increase in crime on hot days does not cause a reduction of crime on other days. In contrast, there could be a "harvesting" effect where extreme heat leads to crime that would have taken place anyway. If these crimes are then "saturated", there might actually be a negative effect in subsequent periods after the contemporaneous heat effect dissipates, for example through incapacitation (Jacob et al., 2007). Huynen et al. (2001) have shown some evidence for such displacement patterns for heat waves on infant mortality with a reduction after the heat wave was over. In this case, heat does not cause more crime overall, but simply shifts the timing of the crime towards hot days.

We study the displacement effect in two ways: At first, we estimate autoregressive distributed lag (ADL) models with different lag lengths L. To test the hypothesis of displacement, we calculate the cumulative effect $CE = \sum_{l=0}^{L} \beta_l$ for windows of 1, 3, and 7 preceding days. We then implement two tests on whether the coefficient is statistically different from zero and/or the contemporaneous effect β_0. Table 7 reports the results for these specifications. We do not find evidence that prior hot days have an impact on crime as neither of the coefficients on lagged temperature is significant in either specification. We clearly reject the null hypothesis that the cumulative effect is not different from zero in the specification with one lag, but we cannot reject it using a longer time horizon. We also cannot reject that the cumulative effect is the same as the contemporaneous effect, indicating that heat does not affect the level of crime outside the daily horizon.[8]

In addition, we aggregate our data to larger temporal units at the weekly, monthly, and yearly level. If harvesting is a concern, we would expect that the positive effect of heat on crime would disappear with longer study periods (Chay and Greenstone, 2003). Table 8 shows results for separate regressions with the main explanatory variable being the number

[8]We further use the distributed lag model to estimate the effect of prolonged heat waves by including interactions of lags with the contemporaneous heat measurement. In neither specification do we find that these interaction terms are statistically different from zero, further strengthening the conclusion that heat acts as a driver of crime over only a very limited time horizon, namely within the same day.

days above 85F for each period. We find positive and significant effects of hot days on crime for each period considered. However, the magnitude of the effect is decreasing over time suggesting that there is some evidence for replacement of crime. Over the course of one year, an additional hot day leads to an increase of 0.17% more crime.

Table 7: Testing for weather lags

	(1)	(2)	(3)
	1 Lag	3 Lags	7 Lags
Max daily temperature	0.000739***	0.000658***	0.000661***
	(0.000184)	(0.000191)	(0.000190)
L.Max daily temperature	-0.000158	0.000136	0.000140
	(0.000210)	(0.000212)	(0.000213)
L2.Max daily temperature		-0.000270	-0.000233
		(0.000268)	(0.000262)
L3.Max daily temperature		-0.0000895	-0.000242
		(0.000201)	(0.000302)
L4.Max daily temperature			0.000189
			(0.000288)
L5.Max daily temperature			0.00000653
			(0.000273)
L6.Max daily temperature			0.00000925
			(0.000225)
L7.Max daily temperature			-0.000159
			(0.000156)
Cumulative Effect	0.000581	0.000434	0.000372
P-value $\Sigma\beta_l = 0$	0.0092	0.1616	0.2784
P-value $\Sigma\beta_l = \beta_0$	0.4531	0.3679	0.2915
R-squared	0.182	0.182	0.182
Observations	2,031,019	2,029,150	2,025,792

Dependent variable: Daily number of crimes by reporting district

Standard errors clustered at the daily level

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 8: The crime and heat gradient at different levels of temporal aggregation

	(1) Weekly	(2) Monthly	(3) Yearly
Number of hot days $\geq$ 85F	0.00758**	0.0350***	0.326***
	(0.00376)	(0.00741)	(0.0375)
PM2.5 concentration	0.00150***	0.000468	0.00419***
	(0.000503)	(0.00150)	(0.000485)
Precipitation	0.00482	-0.0147	1.061***
	(0.0164)	(0.0239)	(0.0712)
Sample Mean	3.499	15.27	183.3
R-squared	0.579	0.825	0.955
Observations	474,308	108,672	9,056

Dependent variable: Daily number of crimes by reporting district

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

A.3 Robustness Checks and Additional Analysis

A.3.1 Robustness to Count Models

In this section, we test for the robustness of our results with regard to count models. In the main section of the paper, we used ordinary least square estimators to estimate the effect of heat on crime. Since we are dealing with neighborhood counts of crime reports, the OLS estimator might not be the most efficient estimator as it assumes normally distributed errors around the expected value. In our case with many zero values, this assumptions is necessarily not satisfied. For this reason, we re-estimate the estimating equations above using a fixed-effects Poisson count regression model model.

Table 9 replicates the results for the fixed effect regressions using the Poisson. The results show the same statistically significant effects that we discovered using the OLS fixed effects model. Column (1) shows the overall increase in crime at higher temperatures. Column (2) and (3) document that this heat-crime relationship is more pronounced in neighborhoods with higher poverty and a higher stock of older housing respectively.

Table 9: Robustness check for Poisson regression

	(1) Baseline	(2) Interaction
Max daily temperature	0.00121***	-0.000605
	(0.000362)	(0.000408)
Daily max temp × Share poverty		0.00610***
		(0.000883)
Daily max temp × Share old housing		0.00179**
		(0.000560)
Precipication	-0.0291**	-0.0284**
	(0.00977)	(0.00975)
PM2.5 concentration	0.00174**	0.00172**
	(0.000653)	(0.000652)
Observations	2,031,859	2,016,442

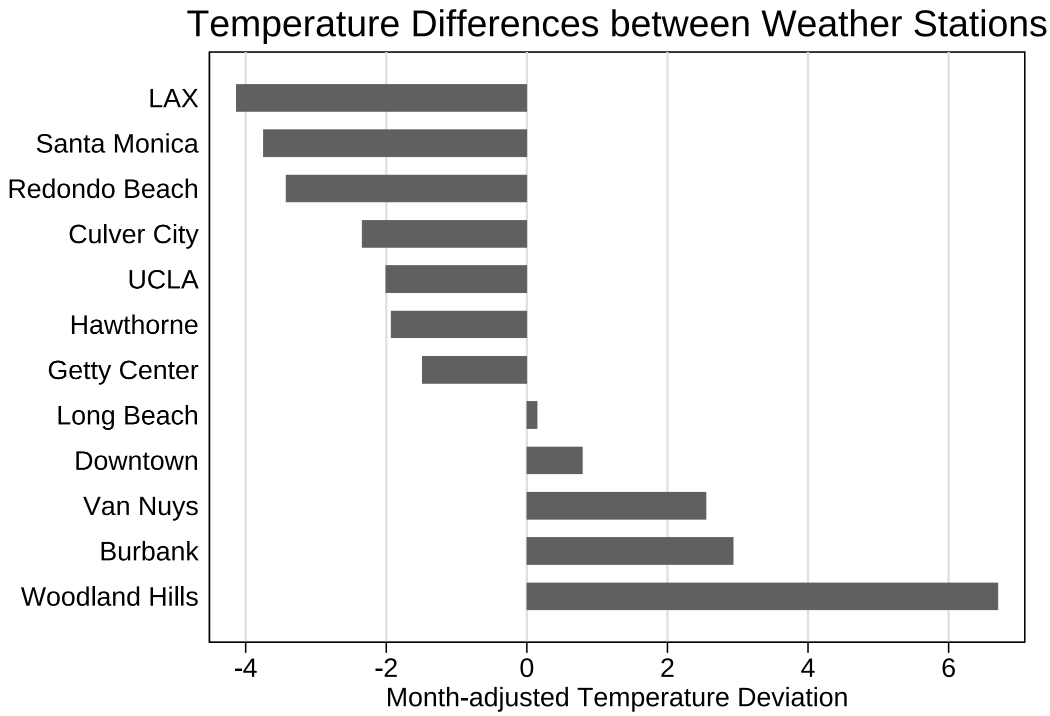
Dependent variable: Daily number of crimes by reporting district
Standard errors clustered at the daily level:
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

A.3.2 Robustness to Temperature Interpolation

In the main section of the paper, we have used nearest neighbor matching to assign temperatures to police reporting districts. While this assures that neighborhood temperature is taken from the most relevant weather stations, it can lead to sharp discontinuities between spatially close neighborhoods if their border is equidistant to two weather stations. In general, temperature patterns in the Los Angeles metropolitan area can vary substantially even over small distances. The presence of the Pacific Ocean and the mountains leads to microclimates with very distinct temperature distributions. These differences are exemplified in Figure 4 which plots seasonally-adjusted mean differences in temperatures of each weather station compared to the overall average.

In this robustness check, we employ inverse distance weighting (IDW) to interpolate temperatures from more than one weather station. Inverse distance weighting employs a weighted average of surrounding weather stations and puts more weight on nearby stations. In our context, we weigh every observation with the normalized inverse difference weight $w_i = \frac{\frac{1}{d_i}}{\Sigma \frac{1}{d_k}}$. We employ a maximum of three weather stations and use only stations that are within a distance of 10 miles. The two interpolation methods do not differ significantly and

Figure 4: Temperature differences in the study area



we find a very high correlation coefficient of 0.98. Table 10 presents the main regression results for temperatures based on the inverse distance weighting scheme. Again, we find sizable and statistically significant effects of increases in daily maximum temperature on neighborhood crime which is stronger in poorer neighborhoods.

A.3.3 Heterogeneity by Crime Victim

We next distinguish crimes by the type of victim. The LAPD crime report data provides demographics of the victim such as gender and race. We distinguish between male and female victims and between victims that are white, Hispanic, and black and perform individual regressions. Table 11 shows that there is no differential effect between female and male victims, and crimes against both genders have similar responses to extreme heat. When looking at heterogeneity by race, we find very similar percentage effects for both white and Hispanic victims. In contrast, the response of crimes against black residents of Los Angeles to high heat is less pronounced and not statistically significant.

Table 10: Robustness check for inverse distance weighting

	(1) Baseline	(2) Interaction
Max daily temperature (IDW)	0.000618**	-0.000486*
	(0.000198)	(0.000198)
Max daily temperature (IDW) × Share poverty		0.00472***
		(0.000541)
Max daily temperature (IDW) × Share old housing		0.000844**
		(0.000288)
Precipication (IDW)	-0.0140*	-0.0136*
	(0.00550)	(0.00551)
PM2.5 concentration (IDW)	0.000971**	0.000974*
	(0.000376)	(0.000379)
Sample Mean	0.532	0.535
R-squared	0.182	0.182
Observations	2,031,859	2,016,442

Dependent variable: Daily number of crimes by reporting district
Standard errors clustered at the daily level:
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 11: Regression results by victim category

	(1) Female	(2) Male	(3) White	(4) Hispanic	(5) Black
Daily max ≥ 85F	0.0112**	0.0118**	0.00734**	0.0144***	0.00246
	(0.00483)	(0.00526)	(0.00324)	(0.00482)	(0.00298)
Precipication	-0.00423	-0.0146*	-0.00161	-0.00402	-0.0101**
	(0.00838)	(0.00804)	(0.00660)	(0.00665)	(0.00404)
PM2.5 concentration	0.000615	0.0000982	-0.0000395	0.000553	0.000134
	(0.000398)	(0.000304)	(0.000190)	(0.000371)	(0.000177)
Sample Mean	0.228	0.244	0.106	0.201	0.0989
R-squared	0.113	0.111	0.129	0.108	0.201
Observations	101,281	101,281	101,281	101,281	101,281

Dependent variable: Daily number of crimes by reporting district
Standard errors clustered at the daily level: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

A.4 Crime Classification

Violent Crimes To classify violent crimes, we incorporate all crime reports that are filed as homicide, manslaughter, battery, assault, rape, arson, kidnapping, and lynching. Table 12 reports the LAPD crime description for each of these cases together with a count of reports for the study period 2010-2017.

Property Crimes To classify property crimes, we incorporate all crime reports that are filed as theft and burglary, or other crimes that are related to other's property such as using credit card fraud and using counterfeit . Table 13 reports the LAPD crime description for each of these crime types.

Table 12: Violent crimes and frequency

Crime code description	**Count (2010-2017)**
BATTERY - SIMPLE ASSAULT	156,610
INTIMATE PARTNER - SIMPLE ASSAULT	92,704
ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT	73,362
ROBBERY	68,596
INTIMATE PARTNER - AGGRAVATED ASSAULT	10,162
ATTEMPTED ROBBERY	9,756
BATTERY WITH SEXUAL CONTACT	8,860
RAPE, FORCIBLE	8,075
CHILD ABUSE (PHYSICAL) - SIMPLE ASSAULT	7,346
CRIME AGAINST CHILD (13 OR UNDER)	6,879
BATTERY POLICE (SIMPLE)	3,757
ARSON	2,841
CRIMINAL HOMICIDE	2,321
OTHER ASSAULT	2,298
KIDNAPPING	1,751
CHILD ABUSE (PHYSICAL) - AGGRAVATED ASSAULT	1,382
ASSAULT WITH DEADLY WEAPON ON POLICE OFFICER	1,352
CHILD STEALING	970
RAPE, ATTEMPTED	934
KIDNAPPING - GRAND ATTEMPT	625
BATTERY ON A FIREFIGHTER	250
LYNCHING	41
MANSLAUGHTER, NEGLIGENT	4

Table 13: Property crimes and frequency

Crime code description	**Count (2010-2017)**
BURGLARY FROM VEHICLE	131813
VEHICLE - STOLEN	131,667
BURGLARY	123,382
THEFT PLAIN - PETTY ($950 & UNDER)	122,033
THEFT OF IDENTITY	107,534
THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER)	70,059
THEFT-GRAND ($950.01 & OVER)EXCPT,GUNS,FOWL,LIVESTK,PROD0036	60,523
SHOPLIFTING - PETTY THEFT ($950 & UNDER)	38,257
THEFT FROM MOTOR VEHICLE - GRAND ($400 AND OVER)	24,689
DOCUMENT FORGERY / STOLEN FELONY	19,966
THEFT, PERSON	11,440
BURGLARY, ATTEMPTED	10,621
BIKE - STOLEN	9,926
EMBEZZLEMENT, GRAND THEFT ($950.01 & OVER)	6,330
BUNCO, GRAND THEFT	5,915
BUNCO, PETTY THEFT	3,605
SHOPLIFTING-GRAND THEFT ($950.01 & OVER)	3,069
VEHICLE - ATTEMPT STOLEN	2,751
BURGLARY FROM VEHICLE, ATTEMPTED	2,461
EXTORTION	1,879
DEFRAUDING INNKEEPER/THEFT OF SERVICES, $400 & UNDER	1,813
THEFT PLAIN - ATTEMPT	1,409
PURSE SNATCHING	1,028
THEFT FROM MOTOR VEHICLE - ATTEMPT	1,003
COUNTERFEIT	731
CREDIT CARDS, FRAUD USE ($950.01 & OVER)	689
PICKPOCKET	668
EMBEZZLEMENT, PETTY THEFT ($950 & UNDER)	491
BOAT - STOLEN	240
THEFT FROM PERSON - ATTEMPT	239
CREDIT CARDS, FRAUD USE ($950 & UNDER	208
DEFRAUDING INNKEEPER/THEFT OF SERVICES, OVER $400	196
THEFT, COIN MACHINE - PETTY ($950 & UNDER)	192
SHOPLIFTING - ATTEMPT	173
DISHONEST EMPLOYEE - GRAND THEFT	141
DISHONEST EMPLOYEE - PETTY THEFT	108
TILL TAP - PETTY ($950 & UNDER)	78
GRAND THEFT / INSURANCE FRAUD	63
PURSE SNATCHING - ATTEMPT	41
THEFT, COIN MACHINE - GRAND ($950.01 & OVER)	36
BIKE - ATTEMPTED STOLEN	31
PETTY THEFT - AUTO REPAIR	20
THEFT, COIN MACHINE - ATTEMPT	19
PICKPOCKET, ATTEMPT	18
TILL TAP - GRAND THEFT ($950.01 & OVER)	15
GRAND THEFT / AUTO REPAIR	12
DISHONEST EMPLOYEE ATTEMPTED THEFT	8