Adapting to Heat:

Evidence from the Texas Criminal Justice System*

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Abstract

Using administrative criminal records from Texas, we show that heat increases crime in a heterogeneous way across neighborhoods with different housing and economic characteristics. The heterogeneity allows us to predict how effective certain forms of adaptation will be at reducing the impacts of climate change on criminal activity. Our simulations show adaptation reducing, but not completely offsetting, these impacts. Differential rates of adaptation across neighborhoods will likely exacerbate the consequences of already unequal exposure to climate change across society.

Keywords: Climate change, adaptation, extreme heat, criminal justice
JEL Codes: Q5, H75, K42, D91.

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1 Introduction

A robust literature demonstrates that heat increases criminal activity, yet our understanding of the role that adaptation can play in moderating this relationship remains nascent.[1] Climate change will increase the frequency and intensity of hot days around the world (IPCC, 2014) and it will consequently, absent adaptation, also increase total criminal activity. The well documented relationship between heat and crime make this a good setting to examine how different adaptive paths shape social welfare.

Evidence for the specific mechanisms through which adaptation will mitigate the adverse effects of heat in all contexts, not only crime, is sparse, despite the abundant evidence that heat has adverse impacts on human well-being (Park et al., 2020a; Hsiang et al., 2017b; Burke and Emerick, 2016; Carleton, 2017; Carleton et al., 2020). We also lack evidence for how adaptation will differ in its speed and success across locations. While it is clear that adaptation will mitigate at least some of the adverse consequences of climate change, this will not be an instantaneous process, some forms of adaptation will require substantial changes to the built environment (for instance, Barreca et al. (2015)). Understanding the speed at which adaptation is currently occurring, and the effects of this pace of adaptation, are crucial for identifying potential instances where policy intervention can productively accelerate adaptation. It may also be the case that differential rates of adaptation exacerbate inequality in the impacts of climate change and warrant a policy response that helps certain groups of people adapt. It is well known that exposure to the extremes of a changing climate is higher at the bottom of the income distribution (Hallegatte et al., 2018) but differences in the rate of adaptation introduce an additional driver of inequality in who will suffer the consequences of climate change. Thus, understanding how heat affects human behavior and how adaptation has worked so far is key to formulating public policies that prepare us for a

[1] For evidence on the relationship between heat and crime in the United States see Ranson (2014); Harries et al. (1984); Anderson (1989); Anderson et al. (2000); Anderson (2001). Other work has extended these findings to middle (Bruederle et al., 2017; Garg et al., 2020) and low income settings (Blakeslee et al., 2018). Heilmann and Kahn (2019) provides one of the first, limited, examinations of the role of adaptation.

hotter world.

Various explanations for why and how heat affects crime have been offered. Early economics work uses a Becker-style model to focus on potential reductions in the likelihood of being caught, because heat increases the costs of police effort, or on the increased relative benefits of crime due to heat-driven reductions in economic payoffs from other activities. Work in psychology, meanwhile, has focused on the role of heat in driving aggressive behavior (Anderson, 1989; Anderson et al., 2000; Baron and Bell, 1976). More recent economics work has examined how the impact of heat on crime varies across neighborhood characteristics, suggesting that heat's differential effects may be a manifestation of differential investment in early childhood coupled with underlying psychological mechanisms (Heilmann and Kahn, 2019).[2]

In this paper, we re-examine heat's impacts on criminal activity using the most comprehensive data set yet brought to bear on this topic. Using data on the universe of more than 10 million arrests across the state of Texas from 2010 to 2017, we examine how heat impacts the commission of crimes. Our data are unique in providing detail at the individual defendant level across a large geographic region, with meaningful temperature variation across space and over time. The richness of our data on individual defendants allows us to better understand how heat affects human behavior and to conduct the most extensive examination to date of how adaptation could mitigate the effects of future climate change on crime.

Our data contain demographic information on the arrested individual, including their home address, race, and date of birth, as well as information on the charge at arrest. Cru-

[2]A psychological mechanism for heat's impact on crime is consistent with the rapidly growing body of literature in economics that shows heat has a meaningful impact on cognitive and non-cognitive skills in a variety of contexts. Stress from any source, along with emotions like anger and sadness, adversely affects judgement, decision making, and cognition (for instance, Keltner et al. (1993); McEwen and Sapolsky (1995); Card and Dahl (2011); Lerner et al. (2015)). The weather, in turn, shapes emotions. Sunshine, for example, has a positive effect on mood (Schwarz and Clore, 1983), in a way that measurably increases optimism among stock market investors (Hirshleifer and Shumway, 2003). Heat also exerts a direct impact on human emotion. Higher temperatures have been shown to increase negative affect around the world (Baylis, 2020; Denissen et al., 2008; Kenrick and MacFarlane, 1986). Lab studies have confirmed existing work suggesting that heat increases aggression (Anderson, 2001; Almås et al., 2019). In other contexts, heat has been shown to decrease cognitive ability and test performance (Wyon et al., 1996; Fang et al., 2004; Seppanen et al., 2006; Cheema and Patrick, 2012; Fesselmeyer, 2019; Park et al., 2020a,b).

cially, these data provide dates associated with major decisions, including the date of offense and date of arrest. Combining these data with detailed daily temperature data allows us to measure the causal effect of heat on the probability of arrest for different types of crime.

Our approach offers several advances on the existing literature. Previous work on the impacts of heat on crime has been restricted by data limitations to focusing either on a wide geographic region with little detail on individual defendants or temporal resolution (for instance, Ranson (2014)), or to using detailed information for a smaller geography, generally a single city (for instance, Heilmann and Kahn (2019); Harries et al. (1984)).[3] Our data have the advantages of both of these approaches. We are able to cover the geographic scope of the second largest state in the United States, with 28 million residents living across an area that is larger than any country on the European continent aside from Russia. Despite this large geographic scope, we are not constrained to analyzing monthly or geographic aggregates of crime. Rather, we have individual-level crime data, including the address at which the defendant resided, on a daily scale. These two factors allow us to examine the impact of heat on crime across a variety of climates and where the entire study area is not subject to the same temperature shocks (as might be the case with data from an individual city).

The individual scale of our data also allows us to conduct richer analyses of adaptation than existing work. Much of existing work has relied on reported crime data (for instance, Ranson (2014); Heilmann and Kahn (2019)) and so uses information about the location of the crime (or report), but not the residence of the defendant.[4] This makes it difficult to link defendants to a specific built environment in order to examine how this built environment might mediate the impact of heat. Because we know the address of the defendant at the time they commit a crime, we are not subject to this limitation and conduct a variety of heterogeneity analyses to understand how income, poverty, and the age of the housing stock

[3]Blakeslee et al. (2018) is a notable exception to this, using detailed daily data for the entire Indian state of Karnataka.

[4]Levy et al. (2020) demonstrates that where someone commits a crime and where someone resides are often different areas. We thus believe that our approach does a better job capturing who is driven by heat to commit crimes than earlier studies.

mediate the relationship between heat and crime.

It is well-known that the short-run response to weather shocks is not an accurate estimate of the impacts of future climate change (Hsiang, 2016) due to the adaptation that will occur in response to climate change. But there is currently little understanding of the mechanisms by which this adaptation will occur and the consequences that it will have for individuals during the period of transition. In much of the existing literature, adaptation is a black box process that simply reduces the negative impacts of, for example, heat on mortality in places that are more accustomed to high temperatures (for instance, Heutel et al. (2021)). Comparing impacts in places at different equilibrium levels of adaptation provides an estimate of the scope for adaptation to reduce impacts, but ignores the process of reaching that equilibrium and how adaptation may occur at differential rates in different places.

Differences in the transitional path to an adapted state may have important welfare implications. For example, consider the seminal work on heat and mortality by Barreca et al. (2015). The paper demonstrates that adaptation in the form of air conditioning has substantially reduced the mortality impacts of heat in the United States over time. The U.S. has now obtained an equilibrium level of adaptation in which mortality from heat exposure is substantially lower than prior to the widespread adoption of air conditioning. But the adoption of air conditioning was not a uniform process and the effects of heat on mortality were reduced differentially for different populations during the transition period. It is possible that this differential rate of adaptation *increased* inequality in the mortality burden of heat during the transition period relative to a counterfactual of no adaption or uniform adaptation..

We examine how the process of adaption will occur and how it will vary across income, race, and ethnicity. We offer some of the first estimates of the distributional consequences of differences in *adaptation*, rather than differences in exposure to climate change. To do so, we measure how the impact of heat varies across different levels of a range of neighborhood adaptation markers and use the variation in impacts to predict the effectiveness of future adaptation. Crucially, we do not assume that levels of adaptation are fixed or that they evolve uniformly. Rather, we predict how adaptation will evolve independently across individual units in our data. Combined with the output of more than 40 global circulation models (GCM), we use these predictions to examine how adaptation evolving at different rates differentially mitigates the impact of predicted changes in exposure to high temperatures in Texas.

Our work confirms that temperatures above 65°F lead to increases in crime. These increases are driven almost entirely by violent crime, with arrests for such offenses as traffic violations and larceny unaffected. The fact that arrests for traffic violations do not increase (or decrease) suggests that we are in fact measuring increases in crime, and not the effect of heat on police behavior.[5] We also do not find any evidence that heat increases police killings of civilians, a proxy for police aggression.

We find evidence that heat not only increases violent crime, but that it does so by interacting with the presence of deadly weapons. Within the violent crime category, heat has some of its largest effects on weapons charges and assault with a weapon. We observe that heat has larger effects on gun-specific charges after January 1st, 2016, when Texas made it easier to carry guns in public places.

Though these heat effects on crime are largest for individuals who live in the poorest census block groups in Texas, they are also significant for those who live in the wealthiest census blocks. The effects, however, are concentrated in block groups with the oldest homes. These are the homes with the lowest levels of air conditioning generally and lowest levels of central air conditioning specifically. Further, when we examine the joint distribution of housing stock age and income, we find that the effects are concentrated in block groups with the oldest housing stock, regardless of income. Effects in the block groups with older housing stocks are relatively consistent across income groups. Thus, the observed variation in the impact of heat across neighborhoods is likely due to differences in the ability of individuals

[5] A companion paper, Behrer and Bolotnyy (forthcoming), examines the impact of heat on non-defendant actors in the criminal justice system, including police, using these same data.

to protect themselves from heat that arise from differences in housing stock, rather than from differences in childhood investments (Heilmann and Kahn, 2019).

We also examine whether heat's impact on all of the outcomes we study varies by the race or ethnicity of the defendant. Focusing on White non-Hispanic, Black, and Hispanic defendants, we do not find any evidence for variation in heat's impact. Heat increases crimes at similar rates for all three groups and crimes increase in similar ways in neighborhoods with a majority population of each of these three groups.

Turning to adaptation, we estimate how future climate change will impact arrests inclusive of the mitigating effects of adaptation. We predict how proxies for the level of adaptation will evolve individually in every block group in our sample from 2030 to 2050, combining these predictions with predictions of how the climate will change from global circulation models. We find that climate change will increase arrests for violent crimes across Texas over this time period. Adaptation reduces the impact of unmitigated climate change by approximately 25%, but even with adaptation annual violent crime arrests still increase by 9% by 2050.

Our analysis confirms that the rate of adaptation is not even across the population. Lower income areas see increases in crime that are roughly 70% larger than high income areas, and majority-minority neighborhoods see increases that are about 20% larger than majority-White neighborhoods. This is a result of differences in the speed of adaptation rather than differences in the physical rate of climate change. Temperatures change at roughly the same rate across all neighborhoods, but adaptation occurs much faster in wealthier, majority-White neighborhoods.

Our results provide a more detailed understanding than the existing literature of how heat's impacts vary across neighborhoods and racial or ethnic groups. These detailed heterogeneities provide additional evidence for the regressive impacts of climate change. They also enable us to incorporate a more informed estimation of adaptation into our examination of how climate change will change crime rates. Our results highlight that both climate mitigation policies (Peng et al., 2021) and differences in climate adaptation can create winners and losers.

The rest of the paper is structured as follows. Section 2 provides the conceptual framework for our study, Section 3 describes the data in detail, and Section 4 lays out our empirical strategy. Section 5 reports the effects of heat on arrests. Section 6 presents estimates for how the probability of arrest will change due to climate change and discusses the role of adaptation in reducing these effects. Section 7 concludes.

2 Conceptual Framework

There is a robust literature both in and outside of economics on the adverse relationship between heat and crime. Hotter days have been shown to increase crime across a range of settings in the United States (Ranson, 2014; Heilmann and Kahn, 2019; Harries et al., 1984; Anderson, 1989; Anderson et al., 2000; Anderson, 2001). Other work has extended these findings to middle (Bruederle et al., 2017; Garg et al., 2020) and low income settings (Blakeslee et al., 2018). In much of this work, heat appears to increase non-property crimes more than property-focused crimes.

Different hypotheses have been advanced to explain this well-documented empirical relationship. Broadly, these can be classified as pointing to a "rational" economic channel for the impact of heat in the mold of Becker (1968) or towards an explanation that focuses on the role that heat plays in reducing psychological control. Arguments in favor of the former mechanism situate the decision to commit a crime in an expected utility framework and focus on the role that heat may play in changing either the costs or benefits of crime. For example, heat may change the effort that police exert in pursuing criminal complaints by making effort more costly (Obradovich et al., 2018) and so reduce the expected cost of committing a crime by reducing the likelihood of being caught. Heilmann and Kahn (2019) uses data on criminal and police activity in Los Angeles to test this hypothesis and finds little support for it. Alternatively, heat may have negative impacts on legal sources of income (for instance, by reducing crop yields) and so increase the benefits of committing crime.

The hypothesis that heat increases criminal activity by reducing psychological control also has a long history. Work in psychology has documented the role of heat in increasing aggression for decades (Baron and Bell, 1976), succinctly summarized by Boyanowsky (1999): "aggression in heat is mediated by emotions, cognitions, and stress from affective-thermoregulatory conflict that produces violently aggressive behavior." These results have been supplemented by more recent work in experimental economics showing the same (Almås et al., 2019). Observational work using billions of data points from Twitter has shown that heat increases negative sentiment (Baylis, 2020) in countries around the world. Arguments for a psychological mechanism linking heat and crime combine the observation that heat can increase irritability, anger, and hostility (Anderson, 1989; Anderson et al., 2000; Denissen et al., 2008; Larrick et al., 2011) with the evidence that a large share of crime, especially violent crime, is due to a non-rational response to stimuli (Heller et al., 2017).

Heat, thus, makes individuals more likely to respond to a given stimulus with violence.[6] This is particularly consistent with the evidence that heat has much larger impacts on violent crimes, or crimes of passion, than property crimes (Ranson, 2014; Heilmann and Kahn, 2019; Blakeslee et al., 2018; Mukherjee and Sanders, 2021). Heilmann and Kahn (2019) suggests that the psychological mechanism can also explain observed poverty and income gradients in the impact of heat on crime due to lower levels of investment in the development of non-cognitive skills in childhood in higher poverty neighborhoods (Fletcher and Wolfe, 2016).

[6] Cohen et al. (2018) suggests that increased consumption of alcohol on hot days drives some of the observed increases in crime. To the extent that alcohol and heat both reduce psychological control, this explanation is not mutually exclusive with the psychological explanation.

3 Data

3.1 Texas Department of Public Safety (TDPS) Data

We use confidential data on arrests reported to the Texas Department of Public Safety (TDPS) by arresting agencies every 7 to 30 days, as required by the Texas Code of Criminal Procedures, Chapter 66.252. Our data span 2010 through 2017 and cover every Texas county. Texas state law requires that counties maintain at least a 90% data completeness rate over a rolling five year period in order to be eligible for certain state funds. Completeness means that the data reflect the most up-to-date status or disposition of each case. We received our data in 2019, so at least 90% of the cases through 2017 have been deemed to accurately reflect their most up-to-date status in our data (Department of Public Safety, 2019).

The TDPS arrest disposition data come in several parts. We combine files providing data on the individual arrested, the circumstances of the arrest, details of any prosecution, details of any court trial, and details of the subsequent sentencing or appeal. The individual data provide a unique ID for each individual arrested in our data, as well as the sex, race, ethnicity, and date of birth. The arrest data include the date of arrest, the date of offense, the arresting agency, the level of the arrested offence (for instance, misdemeanor A), the arrest charge (for instance, manslaughter), and the address of the defendant at the time of the arrest.[7] Each arrest charge is given a unique entry in the data. For example, if an individual is arrested on October 1, 2010 and charged with assault and resisting arrest, we will have two records for that individual, one for each charge. If they are then arrested again in 2011 for another charge, we will have a third entry for them. Each of these incidents can be linked to the same individual with their unique ID and each incident has a unique incident ID.

We drop all arrests and charges for which we do not have court outcome data (i.e., the

[7] About 25% of the arrests do not have a date of offense recorded, so we conduct our analysis using the date of arrest. For the arrests for which we have both date of arrest and date of offense, these dates are the same 84% of the time. We run robustness checks using the date of offense and find broadly similar results.

arrest charge does not have a match in the court data) and charges for which the court has not issued a decision.[8] We also drop misdemeanor C cases as these are inconsistently reported in our data. This leaves us with 2.6 million arrests. We geocode the addresses provided with the address information and match each arrest to the county in which the individual lived when they were arrested. We then collapse the data to the count of arrests at the county-day level. This leaves us with a balanced panel of 742,188 county-day observations from 2010 through 2017. We maintain separate counts of crimes by category of the arresting charge (for instance, violent crimes, assaults, etc).

Arresting charges are defined in the raw TPDS data. When we conduct analyses on total crimes, we pool all of these charges together. We also aggregate some of these charges into violent and non-violent crimes and analyze these separately. We consider the following crimes to be violent: assault, aggravated assault, homicide, manslaughter, kidnapping, domestic assault, and weapons crimes. We define non-violent crimes as: larceny, burglary, stolen property, traffic (excluding those resulting in manslaughter charges), marijuana possession, and marijuana dealing.

Our definition of violent and non-violent crimes is not exhaustive. There are some crimes that we do not consider violent or non-violent. Robbery, for example, is generally defined as "the action of taking property unlawfully from a person or place by force or threat of force." Thus, while clearly a property crime, it might also be considered a violent crime due to the threat or use of force. Not all robberies, however, involve the actual use of force or violence. These crimes are included in our analysis of heat's impact on total crime and we analyze heat's impact on some of these uncategorized crimes individually, but we exclude them from our analyses of violent and non-violent crimes.

[8]These are indicated as cases where the result is "pending" or "no determination." Dropping non-matching court cases drops 11% of the arrests in our raw sample. Including these and conducting our main arrest analysis does not change our results.

3.2 Weather Data

We match our daily arrest counts with daily weather data from the PRISM Climate Group's gridded re-analysis product. The PRISM product provides daily information on minimum and maximum temperature, minimum and maximum vapor pressure deficit, dew point, and precipitation on a 4km by 4km grid for the continental United States. We aggregate these measures to the county level by taking the average across the grid points within the county. We assign daily maximum temperature to one of 12 5°F temperature bins from 40°F up to 100°F. Days below 40°F and above 100°F are included in separate bins. We also bin daily precipitation to control for the impacts of particularly rainy days. We assign days to four exclusive precipitation bins: no precipitation, less than half an inch, one half to one inch, and more than one inch.

3.3 Socio-economic and Neighborhood Data

We collect socio-economic data at the census block group level from the 5-year American Community Survey (ACS) for every year in our sample. We use the geocoded addresses from the arrest data to assign individuals to census block groups and categorize arrests based on the characteristics of the block group in which the defendant lives at the time of the arrest. We focus in particular on median income, the poverty rate, and the median housing age. These allow us to classify arrests as occurring in block groups based on income or poverty rates and by the age of the housing stock, which we take as a proxy for the presence of air conditioning. We also use the share of residents in a block group living in an urban environment to classify block groups as urban or rural. We define block groups as urban if at least 80% of their residents live in an environment defined as urban by the ACS.

3.4 Summary Statistics

In Table 1 we present summary statistics for our primary measure of temperature - daily maximum temperature - for aggregate crimes, and for aggregate crimes by race and ethnicity. Roughly 60% of the days in our sample experience a maximum temperature above 70°F and the majority of days in the sample have no precipitation. Figure A1 shows how days are distributed across temperature bins within an average year across all counties in our sample in aggregate and separately by race and ethnicity. We summarize the spatial distribution of both crimes and hot days in Figure 1. Arrests are broadly distributed across the state.

High temperature is also evenly distributed across the state. We show the average annual number of days over 90°F. Counties in the Rio Grande Valley have, on average, the largest number of these days, but every county in Texas experiences at least 40 such days in an average year. Figure A2 underlines the variation in temperatures within counties across years in our sample and across months within a given year. Panel A shows the number of days above 90°F in each year of our sample for three counties selected from each tercile of the distribution of 90°F+ days. While there is clear separation in the number of days as you move down the distribution - Taylor County never experiences a year with as many hot days as the coolest year in Starr County, and Aransas County experiences only one year matching Taylor's coolest year - there is also clear variation within each county across years in the number of hot days. On average these three counties experience yearly deviations of as many as 25 days on each side of their average number of 90°F+ days.

Looking at the distribution of hot days within the same three counties across months of the year, it is clear there is also variation in when days become hot and cease to be hot within a year. Starr County experiences 50 such days in March during our sample, while Aransas and Taylor experience almost no such days in March. All experience a substantial number of 90°F+ days in August, but while these decline to zero by October in Aransas it takes until January to reach zero days above 90°F in Starr.

There are roughly 250,000 crimes per year in our data and counties experience an average of 2.7 crimes per day over our sample period. White, non-Hispanic individuals commit the largest number of crimes in our data, reflecting their plurality in the overall population. Figure A3 shows that the distribution of crimes across time in our sample is relatively constant. The average number of daily crimes does not vary substantially across years or across months within the average year.

4 Empirical Approach

In all of our analyses, we rely on day-to-day variation in local temperatures within a county to identify the impact of hotter temperatures on our outcomes of interest. Identification rests on the assumption that day-to-day variations in temperature within a county are plausibly exogenous with respect to our outcome of interest. We control for annual trends and month-to-month seasonality in temperature.

4.1 Arrest Analysis

We follow much of the existing literature in assuming that crimes C_{idmy} in county i on day d of month m of year y follow a Poisson distribution (for instance, Ranson (2014)). We assume the standard exponential form for the conditional mean ($\mu\big(\mathbf{X}_{idmy}\big)$) of crimes ($C_{idmy}$) given our covariates ($\mathbf{X}_{idmy}$) and take the logs of both sides to get our estimating equation:

$$log\Bigg(\mu(\mathbf{X}_{idmy})\Bigg) = \beta_k \sum T_{idmyk} + \rho_l \sum R_{idmyl} + \delta_y + \psi_i + \eta_d + \Omega_m \qquad (1)$$

where T_{idmyk} is an indicator for whether the maximum temperature in county i on day d in month m and year y is in the k^{th} temperature bin. We use one bin for temperatures below 40°F and one for those above 100°F. Bins in between are in 5°F increments and we omit the 60-65°F bin. R_{idmyl} is an indicator for whether the day falls in the l^{th} precipitation bin. We omit the highest bin in our estimation. $\eta_d, \Omega_m, \delta_y$, and ψ_i are day-of-week, month, calendar year, and county fixed effects. Our county fixed effects absorb any time invariant location specific determinants of crime. Our daily and monthly fixed effects account for variation in crimes over the course of a week (for instance, there may be more crimes on Fridays) and the year (for instance, there is less outdoor activity in the winter and generally lower crime). Our results are robust to several alternative sets of fixed effects, including a month × year fixed effect. To alleviate concerns about smooth variation in temperature within months, we also show that our results are robust to including a day-of-year fixed effect (see Table A1).

β_k is the coefficient of interest and measures the approximate percentage change in daily crimes if the maximum temperature is in temperature bin k relative to the 60-65°F bin. We cluster standard errors at the county level (Abadie et al., 2017) and weight our regressions by the total population of the county in each year, as captured in the ACS.

We estimate this fixed effects Poisson model using maximum likelihood (Hausman et al., 1984; Wooldridge, 1999; Correia et al., 2019). We choose a Poisson model both because of the count and skewed nature of the outcome crime data and because of the properties of the fixed effects Poisson estimator. Since there are many county-days with no crimes, our data has many zeros. The Poisson model accounts for these zeros more easily than a linear fixed effects model with $\log(C_{idmy})$. It also avoids the bias caused, when the share of zeros is non-trivial, by some common methods of transforming data to account for zeros (Nichols et al., 2010).

In our primary analysis C_{idmy} represents the count of total crimes in a county on a given day. We conduct several alternative analyses to examine how heat impacts different types of crimes or impacts crimes in neighborhoods with different characteristics. In those analyses the specification is the same, but we change the outcome to be the count of crimes in a particular category. For example, C_{idmy} can be the count of violent or non-violent crimes. We also conduct analyses where C_{idmy} is the count of crimes in block groups where the median house was built prior to 1990 or after 2000 or in block groups within various income and poverty bins.

5 Results: Heat and Arrests

We present our results in several sections. We start with the average impact of heat on arrests before examining how heat impacts violent and non-violent crimes individually. We then turn to an examination of how the introduction of an open carry law in Texas in 2016 interacted with heat's impact on crimes related to weapon use. Finally, we examine how the impact of heat varies by neighborhood characteristics, in particular the age of the housing stock and neighborhood income.

5.1 Heat Increases Arrests

Our primary result is that heat increases arrests. We find that arrests increase roughly monotonically as temperature increases from 70°F to 100°F (see Figure 2 and Table A1). Days above 90°F increase arrests by approximately 5% relative to days between 60-65°F. We find a substantial decline in arrests on days below 55°F, consistent with the notion that cooler days discourage the kinds of activities that can lead to crime.[9] These results are robust to alternative fixed effects specifications, including weekend rather than day-of-week fixed effects and county-specific time trends, as well as to controls for humidity like dew point and vapor pressure deficit (see columns 8 and 9 of Table A1). They are also robust to examining weekends separately from week days (Table A2), using data on the date of offense rather than the date of arrest (Table A3), and to including up to 5 lags of daily temperature (Table A4).[10]

[9] In contrast, the mechanisms driving the relationship between temperature and mortality, for example, are physiological rather than economic, and therefore are unlikely to be impacted by changes in activity at lower temperatures. We focus on absolute, rather than relative, measures of temperature because there is little evidence that it is exposure to high temperatures relative to a seasonal average, rather than high absolute temperatures themselves, that have the most adverse effects (for instance, Kim et al. (2021)).

[10] Some existing work has found evidence that heat shifts crimes forward in time (Jacob et al., 2007), such that crime increases on a hot day but declines on subsequent days. We do not find evidence that our effects on violent crime are due to shifting. In Table A5, we show that temperatures do not appear to impact the number of violent crimes on the subsequent three days.

5.2 Heat's Impacts are Largest for Violent Crime Arrests

We find the impact of heat on total crime is driven almost entirely by heat's impact on violent crime.[11] As Figure 3 shows, hot temperatures substantially increase violent crime, with a day above 100°F increasing violent crimes by more than 10%. We do not find impacts of heat on non-violent crime that are significantly different from zero for any of our high temperature bins. These results are strongly suggestive that the impact of heat on crime operates by increasing aggression. Cool days appear to influence violent and non-violent crimes similarly, providing support for the hypothesis that the reduction in crimes on cool days is due to reductions in activity outside of the home.

To assess how much of our effect is driven by hot days leading to more activity outside of the home, we look at the impacts on crime of days that are both high temperature and high precipitation days (see Figure A5). We find that the effects of temperature on these days are attenuated across the entire temperature distribution. Days between 65°F and 80°F no longer have a significant impact on crime if there is also high precipitation, consistent with the idea that the effects at these mild temperatures are driven primarily by increased human interaction. However, our effects at higher temperatures are robust to looking at temperature's impact on high precipitation days, with effects roughly 2/3rds the size of our base effect. This is consistent with the hypothesis that there is both a psychological and a human activity mechanism at play in how heat increases crime.

The richness of our data allows us to examine how heat impacts detailed categories of violent and non-violent crimes as well (for a discussion of non-violent crime results see Appendix 1). These detailed results indicate that the increase in crime is driven specifically by increases in assaults (Figure A6). Both aggravated assaults and assaults increase by between 10 and 20% at high temperatures. Heat also appears to significantly increase the frequency with which individuals reach for weapons, with both general weapons crimes and

[11] Figure A4 shows the count of a selection of specific violent and non-violent charges in our sample. While the most common crimes are traffic related, assault and aggravated assault are also among the most common crimes in our data. In general, both violent and non-violent crimes are well-represented in our data.

aggravated assaults with a weapon increasing by between 10 and 20% on very hot days.[12]

5.3 Heat's Impacts are Amplified by Open-Carry

To further examine whether heat interacts with the presence of weapons we examine how the impact of heat on weapons charges changes after January 2016, when Texas made it significantly easier to carry weapons.[13] The law likely made guns more salient and may have made it more likely for individuals impacted by heat to reach for guns. We have shown that heat appears to increase violent crimes, most likely due to the documented impact of heat on mood, cognition, and aggression. If guns became more easily accessible in the heat of the moment after 2016, this may have increased the frequency of crimes that involve a gun.

To test this hypothesis, we specifically examine instances where individuals are charged with crimes like "brandishing a weapon." We use the same Poisson fixed effects specification described in the analysis of heat on crimes, but we make two minor changes. First, we increase our temperature bin size to 10°F and group all temperatures above 90°F. We do this because there are relatively few gun-related arrests in our data and finer bins result in a lack of power, particularly at the highest temperatures. Second, we estimate an event study specification where we examine how the impact of a day in each temperature bin changes after January 1^{st}, 2016.

We find that after 2016 the impact of a day over 90°F on gun crimes increases by between 14% and 39%. By comparison, we see a 1% increase in the impact of heat on assaults and a 2% increase in the impact of heat on aggravated assaults (Table 3).[14] The range in effects is

[12]While other violent crimes increase - in particular homicides and kidnapping - our estimates of these increases are much less precise than our results on assaults. However, this imprecision is likely due to a relatively small number of these kinds of crimes in our data. For example, our data include roughly 5,000 homicides, but more than 100,000 assaults.

[13]Texas House Bill 910 went into effect on January 1^{st}, 2016, allowing for the open-carry of handguns in areas in which only concealed-carry had previously been permitted. The law did not change the types of guns that were legal to possess or the process for acquiring a gun or a concealed-carry permit. It simply made it legal to openly carry a gun that previously had to be concealed. This made it easier to legally carry a gun in public and made weapons more visible. It may have also made it more likely for gun owners without permits to carry their guns in the expectation that police would assume anyone carrying a weapon had a permit.

[14]Gun charges are their own category of charges (for instance, "brandishing a firearm") and not a subset

generated by differences in how we define a gun crime. The smaller effect is estimated on a broad subset of crimes related to weapons. The larger impact is estimated using a subset of crimes that we believe were particularly likely to be impacted by the law change.[15] Both of these results indicate that heat has a larger impact on the commission of gun crimes after 2016 than before, not that gun crimes increased by 14%-39% after the passage of the law. In other words, if prior to 2016 a day above 90°F led to a 10% increase in gun crimes relative to a 60-65°F day, our conservative estimate suggests that after the passage of the law the same day led to an 11.4% increase in gun crimes relative to a 60-65°F day.

We cannot rule out that this increase in the sensitivity of gun crimes to heat was due to something other than the policy change. However, we believe this is strongly suggestive evidence that by reducing the administrative requirements for carrying a gun in public, and therefore increasing the number of individuals carrying handguns outside their homes, the 2016 law substantially increased the likelihood that individuals reached for a gun when aggravated on a hot day. The lack of a meaningful change in the impact of a 90°F+ day on either assaults or aggravated assaults suggests that the increase we observe is not due to a general increase in policing following 2016 or a secular trend in the number of violent crimes.

Our findings are in line with concurrent work by Colmer and Doleac (2022), which utilizes geographic differences to show that more restrictive gun laws mitigate the impact of heat on homicides. Also related is work by Donohue et al. (2022), which finds Right-to-Carry laws increase violent crime through gun thefts and lower police effectiveness. Our approach focuses on a specific policy change, that of making open-carry easier, and on crimes that directly involve gun usage. We find effects on crimes directly affected by the policy change that are smaller (14-39% vs. 50%) than what Colmer and Doleac (2022) finds on homicides writ large. The difference could be due to the fact that Colmer and Doleac (2022) bundle different levels of open-carry restrictions into a binary variable, whereas we look at a marginal change in restrictions. It is also possible that the effect in our setting will grow over time,

of assaults or aggravated assaults.

[15]The list of these specific charges is included in Table A11.

as Texans become more aware of the increased ease of openly carrying guns.

5.4 Heat Impacts by Neighborhood Characteristics

The impact of heat on individuals, and their psychological state, is likely mediated through their built environment. Changes in the built environment are likely to be a key adaptation to climate change. A detailed understanding of how the built environment mediates the effects of heat today provides insight into the capacity of adaptation to reduce the negative impacts of climate change.

While we do not have data on the specific structures in which defendants reside, we can study the characteristics of the census block groups in which they live. Block groups are the second smallest census unit and contain between 600 and 3,000 people. We assign the characteristics of these block groups to defendants who reside in them and analyze how variations in neighborhood characteristics mediate the impact of heat on crimes.

We focus our analysis on two neighborhood characteristics: the age of the housing stock and median income. We choose neighborhood housing age as the best proxy for the presence of air conditioning, a frequently suggested adaptation to mitigating the impact of heat on cognitive and non-cognitive skills (Park et al., 2020b).[16] We can and do examine whether housing age acts as a good proxy for the presence of air conditioning using CoreLogic data.[17] In Figure A9, we show that while more than 95% of new houses in Texas have central air, the penetration among houses built prior to 1980 averages around 80%. Conditional on having any air conditioning, older houses are also more likely to have window or other non-central air conditioning units. Further, while we cannot test this directly, it is plausible that older houses have worse insulation and are less well sealed against the outside environment,

[16]Housing age is also correlated with other determinants of behavior, in particular lead paint. We examine whether there are larger effects in areas with houses built prior to the phase out of leaded paint and find no differential effects.

[17]CoreLogic data are proprietary data on the U.S. property market that we access through Stanford University's subscription. These data are assembled primarily from mortgage applications and include details about the financed properties. The data set does not include information on every property in Texas, but it does cover more than five million parcels there.

making air conditioning less effective in older houses.

Turning to income, higher impacts in lower income neighborhoods may be expected as a result of lower penetration of air conditioning or lower utilization of the air conditioning that is possessed (Davis and Gertler, 2015). Housing quality along other dimensions may vary with income in ways that increase the impact of heat as well. To examine how the impact of heat varies by income, we assign block groups to income quartiles within each year based on their median income relative to other block groups in the same year.

We focus here on an examination of the joint impacts of income and housing age. Because these two neighborhood characteristics are highly correlated, Heilmann and Kahn (2019) is unable to fully separate their impacts on the relationship between heat and crime.[18] While we lack experimental variation in housing age across income bins, the scope of our data provides broader support across all combinations of housing age and income bins and allows us to conduct a deeper examination of their joint impact. Doing so can help us determine whether the observed income gradient in the impacts of heat on crime is driven by correlation between income and housing quality (and adaptive capacity), or by lower levels of investment in childhood education programs in lower-income neighborhoods. To tease apart the individual impacts of building age and income, we separately examine the impact of heat on arrests in block groups in each income quartile and with housing stock built before 1990 and after 2000.[19] To deal with the imprecision that comes from having smaller cell sizes, we widen our temperature bins from five degrees to ten degrees.

On average, we observe the largest impacts in older neighborhoods within each income quartile.[20] There is no statistical difference between the impacts of a day above 90°F on

[18]When we examine block group income and housing age independently, we find that heat has much larger impacts in older and lower-income neighborhoods, consistent with the results in Heilmann and Kahn (2019). We discuss these results at length in Appendix 2.

[19]In these analyses we omit neighborhoods with housing stock built between 1990 and 2000. The correlation between neighborhood housing age and income in our sample is not especially high ($\rho \approx 0.3$). Moving from the median to the 90^{th} percentile of the housing age distribution increases median income by about 25% or moves one from the median of the income distribution to roughly the 65^{th} percentile.

[20]We present results for heat's impact on arrests for violent crimes in Table 2 and leave results on total crime and nonviolent crime for Tables A7 and A8. In all three cases, the pattern is the same.

violent crimes in neighborhoods with older housing stock across all four income quartiles.[21] In these neighborhoods, a day above 90°F increases violent crime by roughly 13%. In newer neighborhoods, with the notable exception of our estimates for the second income quartile, hotter days lead to no increase in violent crime in any income quartile.

Our results have the opposite implication of those in Heilmann and Kahn (2019), which, to the extent they unpack the joint impact, suggest that income is slightly more important than housing age in determining the effect of heat on crime. Our results indicate that it is the quality of the built environment, rather than income, that drives differences in the impact of heat on violent crime. The observed gradient in heat's impact across neighborhoods of different incomes, when testing income individually, appears to be driven by the correlation between neighborhood income and housing quality.

Housing age and income are not the only neighborhood characteristics that may be important in determining how criminal activity responds to higher temperatures. We examine whether the relationship differs in rural and urban neighborhoods or those with higher levels of baseline violence. We also examine whether heat has differential impacts by race or ethnicity. We discuss these results in Appendix 3, but find no major differences across rural and urban neighborhoods, by baseline levels of violence, or by race and ethnicity.

6 What Can We Expect From Climate Change?

Climate change, even under the most optimistic scenarios (see Figure A12), is expected to result in an increase in the number of days over 70°F by mid-century (2050). We've shown that such days increase arrests for violent crimes relative to days between 60°F and 65°F. We should thus expect an increase in arrests for violent crime due to increased temperatures by mid-century. However, as temperatures increase, individuals and society will adapt to mitigate at least some of the impacts of these hotter temperatures. These adaptations will

[21] Consistent with our hypothesis that high incomes don't fully offset the effects of older housing Burke et al. (2022) finds that older housing has higher rates of infiltration (which implies construction that makes AC less effective).

take many forms, but two relevant ones are the increased installation of air conditioning (the extensive margin response) and improved housing conditions that make cooling less costly and more efficient on the intensive margin (for instance, better insulation, passive cooling, central air vs. window units, etc.). As a result, the increase in violent crime arrests is likely to be smaller than a naive projection of our marginal impacts would suggest. It is even possible, if adaptation is sufficiently effective, that the number of arrests due to hotter temperatures is smaller by mid-century than today.

Different areas will, however, adapt at different rates. Wealthier areas may be more able to adapt because of better access to credit to make the necessary investments. These differences in adaptive capacity increase the dimensions along which the impacts of climate change may be regressive. It is well known that poorer areas are more exposed to marginal climates and are likely to be more exposed to future climate extremes (Hallegatte et al., 2018; Hsiang et al., 2017a). But even if more vulnerable areas are not more exposed to future climate extremes, the impacts of climate change may be regressive if these areas are less able to adapt as effectively as a wealthier or less vulnerable area.

To examine this question, we account for the adaptive response to climate change in concert with projections of how future increased temperatures will impact arrests for violent crimes. We allow adaptive responses to evolve individually for every administrative unit in our data, in line with their baseline income and housing quality, as in Carleton et al. (2020). This approach allows us to examine the regressivity of future exposure to temperature and account for the adaptive response of an individual block group. Our projections for future temperatures come from data created by Rasmussen et al. (2016) and used in Hsiang et al. (2017a). These data collect the output of between 28 and 44 global circulation models (GCM) for each of the RCP scenarios and measure the number of days the maximum temperature is in each of the 1°C bins for every county in the continental United States from 1981 to 2100. We use data on temperatures in Texas from 2000 to 2050 to examine how future climate change will change arrests.

In line with existing work (for instance, Heutel et al. (2021)) we measure adaptation by examining how the marginal impact of hot days varies across different areas within our sample that we believe are more or less adapted. This approach captures adaptation to the extent that more adapted areas suffer smaller consequences from a given hot day than less adapted areas. The gradient in effects between more and less adapted places reveals how much we can expect adaptation to moderate the impacts of future climate change.

Our results in Section 5.4 suggest that impacts decline in areas with higher incomes and newer houses. We use both measures, plus their joint distribution, to examine adaptation. Higher levels of income likely enable more retroactive protective investments (for instance, installation of air conditioning in older housing) (Davis and Gertler, 2015), while newer housing stock is more likely to have air conditioning. The joint distribution of income and building age may capture variation in adaptive choices (for instance, how often to run AC vs. whether or not to install it) that is missed by income and housing age individually. For all three measures of adaptation we estimate the marginal impact of maximum temperatures in 10°F bins separately across four quantiles of the income distribution, across three bins of housing age, and across the joint distribution of both. For full details see Appendix 4.[22]

To measure future adaptation, we assign block groups to future income and building age bins based on projections of their current levels of income and median building age and the growth rate of these levels over our sample. We detail these projections in the Appendix. We estimate two different scenarios: (1) A base scenario in which incomes and building age evolve according to the observed growth rates in our sample and (2) a "high adaptation" scenario in which we assume that they will evolve at a growth rate 10x higher than what we have observed. We calculate the impact of temperature on arrests for violent crime as the change in violent crime arrests due to changes in temperatures in every year from 2030 to 2050 relative to the 2000-2010 average, times the marginal effect in each bin according

[22] Past work has found that historic exposure to temperature is a meaningful predictor of adaptation (Heutel et al., 2021) We consider historic exposure to high temperatures, but do not find evidence that hotter areas within Texas are more adapted than less hot areas (Table A12).

to the level of income, building age, or both in the given block group-year. We do this for the temperature projections from each of the climate models in our data under the RCP2.6, RCP6.0, and RCP8.5 scenarios. Our mean projections are the average of the projections within each RCP scenario across all model runs.

We find that adaptation reduces the impacts of heat on violent crime, but does not eliminate the impact of heat or temperature more generally. In the RCP6.0 scenario, for example, assuming that income and building age evolve at their current growth rates, we find that without adaptation climate change will lead to approximately a 12% increase in violent crime arrests by 2050. When we consider our income-based measure of adaptation, this falls to 11%. Considering adaptation measured by building age or the joint distribution of building age and income further reduces the impact to about 9%. This represents a meaningful 25% reduction in violent crime arrests, but does not indicate that adaptation will eliminate the impact of temperature on violent crime arrests. It may, however, slightly understate the true impact of adaptation. As we show in Panel A of Figure 4, the gap between the base (no adaptation) scenario and the joint (considering both building age and income) adaptation scenario varies from year to year and the total reduction in violent crime arrests over the period 2025-2050 due to adaptation is likely larger than 25%.

The impacts of future warming are likely to be unevenly distributed. In Panel B of Figure 4 we show how our projected impacts vary by race and ethnicity. We consider where in Texas the average person of each racial or ethnic heritage lives and allow incomes by these groups to evolve separately. Our estimates of the annual percentage increase in arrests for violent crime by race lie within the same confidence intervals, but our point estimates suggest that White, non-Hispanic Texans may be less impacted by future warming than Black or Hispanic Texans.

However, these annual percentage estimates disguise differences in the total, aggregate impact that climate change will have on these groups. When we calculate the projected total increase in arrests for violent crimes over the period from 2020 to 2050, we find meaningful and statistically significant differences by race and ethnicity. Specifically, Black and Hispanic Texans experience 25.2% (t-value: 8.6) and 21.0% (t-value: 9.4) more violent crime arrests than White Texans over this time period, respectively. These differences are driven by differences in the level of adaptation that we project among Black and Hispanic communities relative to White communities. They do not appear to be driven by differences in future exposure across these groups (Table A13).

Separately from disparities in impacts by race and ethnicity, we find substantial disparities in impacts by income as well. Areas with below median household income today will experience 69.0% (t-value: 9.8) more arrests for violent crime from 2020 to 2050 than areas above the median household income. This again appears to be driven by the slower uptake of adaptation among lower income communities rather than by differences in exposure by income (Table A13).

These results highlight the fact that climate change is likely to have significant distributional consequences due not only to differences in exposure, but also to differences in adaptive capacity. We estimate substantial differences in total impact across income, racial, and ethnic groups despite the fact that our projections suggest that in Texas these groups will be exposed to similar increases in hot days. Adaptation itself will not necessarily reduce the disparate impacts of climate change and may increase them as some areas or communities are more able to adapt than others.

One might have expected adaptation to have a larger mitigating impact than what we measure here. So what is driving these relatively small impacts of adaptation? First, a brief note about what is not driving the results. Our results are not due to the lack of a gradient in the marginal effect of a hot day between the least and most adapted areas. The marginal impact of a 90°F day in low income areas is 55% higher than in high income areas. In block groups with older houses, the marginal effect of the same day is 423% larger. The gap between the most and least adapted areas using the joint distribution of income and building age is similar. Areas with newer houses do appear to be better adapted to heat, with marginal effects of hot days that are close to zero.

Rather, our results appear to be driven by the slow take-up of adaptation as measured by our projections and the changes in the full distribution of temperature. As we show in Table A14, in our base scenario the average block group has not reached the highest level of adaptation as measured by income or building age by 2050. This relatively slow growth in income and slow rate of housing turnover appears to be a major driver of the small mitigating impacts of adaptation by 2050. A second important factor is the overall shift in the temperature distribution. Our estimates indicate that temperatures across the distribution have an impact on arrests for violent crime. Days above 70°F generally increase arrests, while those below 60°F generally reduce them. This implies that the increase in arrests due to more days above 70°F in the future is only half the story. The reduction in days below 60°F will also lead to an increase in arrests for violent crimes. As we show in Panel C of Figure 4, future climate change will lead to substantial increases in days above 70°F along with nearly equal declines in the number of days below 60°F. This does not totally offset the benefits of adaptation to higher temperatures (Panel D, Figure 4), but it does reduce some of the benefits.

Our results under the aggressive adaptation scenario, in which we impose that income and building age grow at 10x the observed rate, are qualitatively similar (Figure A14). Under this scenario, all block groups have new housing by 2050 and the overwhelming majority are in the highest income bin (Figure A14). However, the overall impact of heat under the joint adaptation scenario is still positive and still increases violent crime arrests by more than 5%. In the aggressive adaptation scenario, the reduction in low temperature days is even more important than in the base scenario. Adaptation substantially reduces the impact of days above 90°F, but this is offset by increases in arrests due to reductions in cool days. Importantly, even in the aggressive adaptation scenario, there remain large gaps in impacts across income, race, and ethnicity. Areas with below median household income today still experience 17.4% (t-value: 5.4) more arrests under an aggressive adaptation scenario, while

Black and Hispanic Texans experience 19.9% (t-value: 5.3) and 11.3% (t-value: 5.4) more violent crime arrests respectively than White Texans.

Overall, our examination of adaptation suggests three things. The first is that unabated, climate change will increase the number of arrests of violent crimes and increase the probability that individuals end up convicted of violent crimes (Behrer and Bolotnyy, forthcoming). This is due both to the increase in hot days as well as to the reduction in cooler days. However, the second implication is that adaptation will mitigate some of these effects. In our base scenario, adaptation reduces the impacts of increased temperature by about 25% relative to a simple projection of our pooled estimates. The third implication is that adaptations may be able to further reduce these impacts, but income growth and housing stock turnover will need to be faster than what has been observed in the past. We take this as suggestive evidence of a role for policy to encourage adaptive investments. The historic rate of building turnover, in particular, at least in part reflects observed changes in climate over the last 20 years. If the current trend continues, however, there will be a substantial benefit from adaptation "left on the table" by mid-century. Policy may be able to encourage faster turn-over or uptake of adaptive investments, capturing benefits that might otherwise be unrealized.

Our results also highlight the fact that climate change will shift the entire temperature distribution and reductions in low temperatures, not just increases in extremely hot temperatures, may also have adverse impacts depending on the outcome being examined. We observe substantial increases in arrests due to reductions in cooler days by mid-century, so while it may be generally true that reductions in cold temperatures will lead to improved outcomes (for instance, workplace safety), this will not always be the case.

7 Conclusion

We study how the adverse effects of heat on cognition, mood, and emotional state in turn affect criminal behavior. We find that heat significantly increases arrests, especially for violent crimes. Heat additionally interacts with the presence and availability of weapons. When the Texas open-carry gun law goes into effect in 2016, hot days see a 14-39% increase in gun crimes, compared to a 1-2% increase in non-weapon related assaults.

Our findings show that universal climate control is not a panacea when it comes to mediating the effects of heat on emotion, cognition, and behavior. Adaptation through increases in income and construction of new housing has the potential to blunt the effects of heat on violent crime by over 25%. On current trends, however, adaptation will not eliminate these effects. Differences in the rate of adaptation across vulnerable and non-vulnerable communities may make the realized impacts of climate change more regressive than simple changes in exposure would suggest.

Policy-driven approaches to adaptation may both increase the mitigating impact of future adaptation and reduce disparities across communities, ensuring that future impacts of climate change are reduced for all Texans. Policies that make weapons less readily available in heated moments or facilitate investments that accelerate the turn-over of old, inefficiently cooled housing stock will help communities further adapt to the increasing frequency of hot days. Without additional adaptation, however, we estimate that Texans in an RCP6.0 world will see their annual probability of arrest and conviction increase by 12%.

8 Tables and Figures

8.1 Tables

Table 1: Summary statistics

	Mean	SD	Min	Max
Annual averages of weather measures				
T above 100F	17.10	20.18	0	138
T 95-100F	36.75	14.41	0	94
T 90-95F	49.50	13.36	8	102
T 85-90F	45.26	12.17	13	121
T 80-85F	42.94	10.34	17	80
T 75-80F	37.18	9.06	13	87
T 70-75F	31.75	7.15	11	60
T 65-70F	27.26	6.24	9	46
T 55-60F	17.07	5.33	2	37
T 50-55F	13.06	5.32	1	31
T 45-50F	9.15	4.48	0	24
T 40-45F	6.50	3.99	0	21
T below 40F	8.89	8.15	0	38
Days with no prec	232.53	31.23	125	313
Days with less than 0.5 in	19.67	7.49	1	64
Days with 0.5 to 1 in	5.78	2.70	0	17
Days with>1in	107.27	28.44	25	201
Daily crime averages				
Total crimes	3.24	11.10	0	213
Violent crimes	0.57	2.10	0	46
Non-violent crimes	1.59	5.65	0	137

Notes: We aggregate our weather variables to the annual level and report averages across all counties and years in the sample. Thus, "Mean", for example, indicates the average number of annual days in a temperature bin across all counties and years in the sample. Daily crime average statistics are daily averages across all Texas counties.

TABLE 2: Impact of heat on violent crimes by income and building age

	1^{st} quartile		2^{nd} quartile		3^{rd} quartile		4^{th} quartile	
	Pre-1990	Post-2000	Pre-1990	Post-2000	Pre-1990	Post-2000	Pre-1990	Post-2000
T above 100F	0.120	-0.156	0.137	0.465	0.136	-0.104	0.077	0.025
	(0.028)	(0.103)	(0.027)	(0.225)	(0.029)	(0.093)	(0.037)	(0.055)
T 90-100F	0.111	0.011	0.108	0.357	0.125	-0.037	0.091	0.011
	(0.017)	(0.097)	(0.018)	(0.119)	(0.029)	(0.015)	(0.062)	(0.030)
T 80-90F	0.080	-0.003	0.085	0.074	0.097	-0.020	0.120	-0.002
	(0.011)	(0.042)	(0.010)	(0.076)	(0.023)	(0.032)	(0.056)	(0.020)
T 70-80F	0.048	-0.069	0.035	-0.055	0.017	-0.004	0.085	0.017
	(0.011)	(0.082)	(0.021)	(0.041)	(0.018)	(0.020)	(0.032)	(0.024)
N	672,060	99,348	721,734	131,490	701,280	189,930	479,208	175,320
Outcome mean, T60-65	0.17	0.00	0.13	0.01	0.09	0.02	0.04	0.03
Fixed Effects:								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTES: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimate indicates the percent change on days in each bin relative to the baseline in the omitted bin. Building age refers to the median year (Pre-1990 or Post-2000) of home construction in the block group in which the arrested individual resided at the time of arrest. Income quartiles indicate the quartile of the block group in which the arrested individual resided. We calculate quartiles each year based on the distribution of median incomes by block group. The first quartile includes the lowest income block groups. Quartile thresholds vary by year.

TABLE 3: Change in gun crime charges after 2016

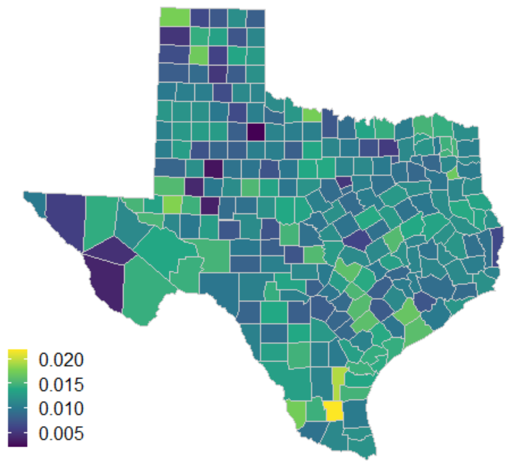
	Gun charges	Narrow gun charges	Assault charges	Agg. assault charges
T above 90F=1 × Post 2016=1	0.144	0.391	0.009	0.003
	(0.033)	(0.095)	(0.024)	(0.066)
T 80-90F=1 × Post 2016=1	0.017	0.129	0.018	0.022
	(0.044)	(0.125)	(0.013)	(0.043)
T 70-80F=1 × Post 2016=1	-0.009	-0.001	-0.017	-0.058
	(0.030)	(0.056)	(0.015)	(0.036)
N	709,307	601,940	734,151	702,732
Fixed Effects:				
County	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes

NOTES: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parenthesis. All regressions are weighted by the total population in each county-year. Coefficents for bins below 70°F are suppressed for parsimony but all regressions include the full set of temperature bins and the full set of precipitation bins. 100× the coefficient estimates indicate the percent change in the impact of a day in each temperature bin on arrests relative to a day in the omitted bin after 2016 relative to pre-2016. "Gun charges" refers to all charges that we categorize as involving guns based on there National Crime Information Center (NCIC) and Texas Uniform Offense Classification codes. "Narrow gun charges" refer to those charges that are specifically related to possessing, discharging, or displaying a gun. Assault and aggravated assault charges are categorized based on their NCIC and Texas Uniform Offense Classification codes.

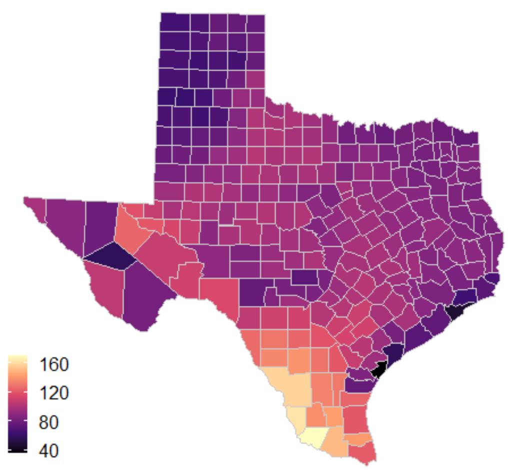
8.2 Figures

Figure 1: Maps of arrests and heat across Texas

(a) Average annual arrests

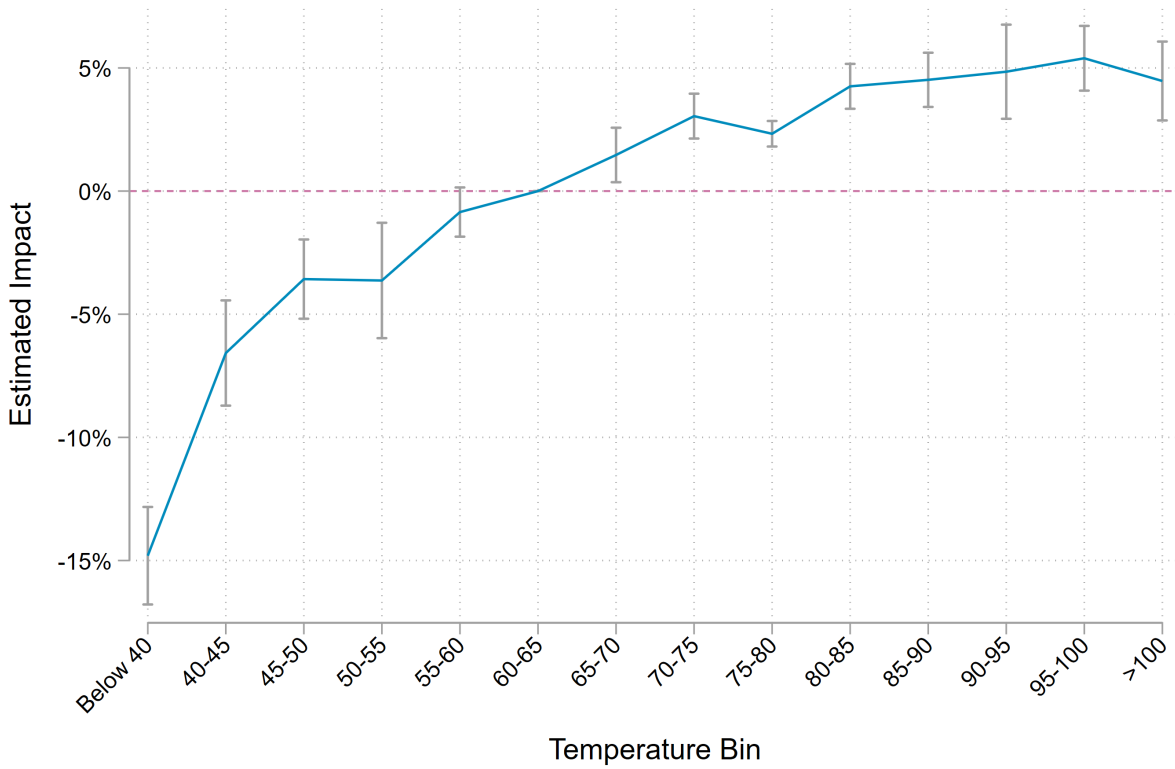


(b) Days > 90°F



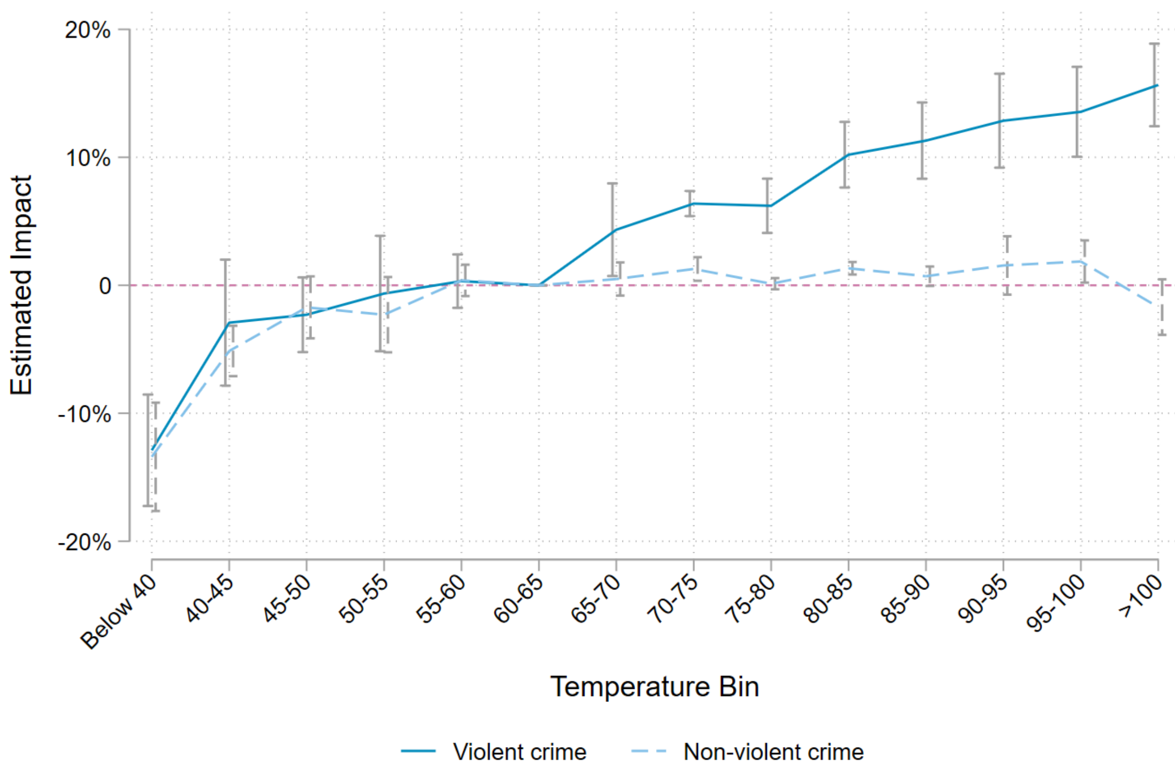
Notes: Panel A reports the average annual number of arrests per capita in each Texas county from 2010 to 2017. Panel B reports the average number of > 90°F days by county per year over the same time period.

Figure 2: Effect of heat on total crime



Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level. Y-axis shows the fraction decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control for precipitation in 3 bins and cluster errors at the county level.

Figure 3: Effect of heat on violent and non-violent crime

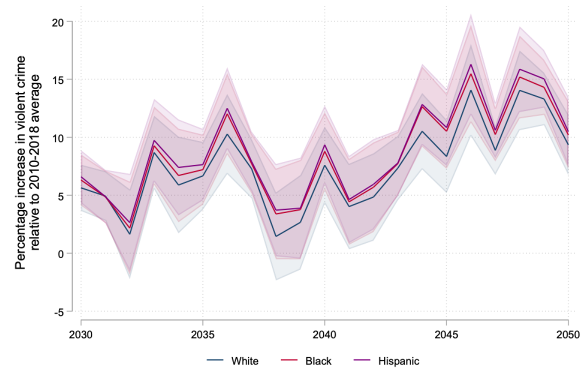


Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control for precipitation in 3 bins and cluster errors at the county level. We weight by the total population in each county-year. Violent crimes are: manslaughter, homicide, kidnapping, sexual assault, domestic assault, aggravated assault, and assault. Non-violent crimes are: burglary, larceny, traffic (excluding those resulting in manslaughter charges), stolen property, possession of marijuana, and dealing marijuana.

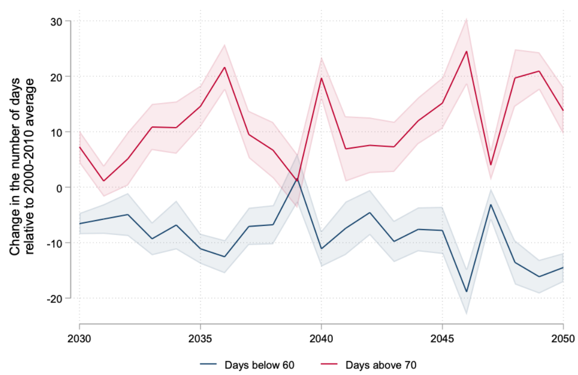
FIGURE 4: Future impacts and adaptation

(A) Impacts by adaptation measure

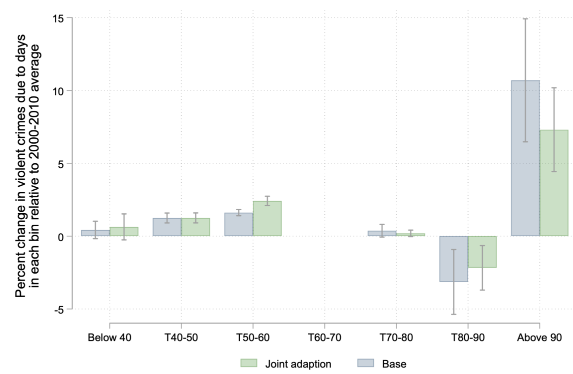
(B) Adaptation inclusive impacts by race



(C) Change in days above and below 60°F-70°F



(D) Future impact by temperature bin 2050



textbfNotes: In all panels we show results using projections under the RCP6.0 scenario and our base adaptation scenario. For RCP2.6 and RCP8.5, see Figures A12 and A13. For results under our aggressive adaptation scenario, see Figure A14. We grow incomes and housing stock age according to block group-specific growth rates in Panel **A** and **D**, and race and ethnicity-specific growth rates in Panel **B**. For results using national and Texas averages, see Figure A11. In Panel **A**, we show the average percentage increase in violent crime across all of Texas due to the increase in average temperatures under four scenarios: using our pooled marginal estimates, using estimates that account for adaptation measured by the median building age, using estimates that account for adaptation measured by income, and using estimates that account for both building age and income. In Panel **B**, we show how the estimates accounting for both income and building age vary by race and ethnicity. Panel **C** shows how the number of days above 70°F, which generally increase crime, evolve compared with days below 60°F, which generally reduce crime. Panel **D** shows the product of our marginal effects by bin and the average total number of days in that bin in 2050 in the base scenario and the scenario accounting for building age and income. The 60°F-70°F bin is omitted. In all cases we plot the average effect across all temperature models and show the 95% confidence interval defined by the standard deviation of estimates across all temperature models.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge (2017), "When should you adjust standard errors for clustering?" Technical report, National Bureau of Economic Research.

Almås, Ingvild, Maximilian Auffhammer, Tessa Bold, Ian Bolliger, Aluma Dembo, Solomon M Hsiang, Shuhei Kitamura, Edward Miguel, and Robert Pickmans (2019), "Destructive behavior, judgment, and economic decision-making under thermal stress." Working Paper 25785, National Bureau of Economic Research, URL `http://www.nber.org/papers/w25785`.

Anderson, Craig A (1989), "Temperature and aggression: Ubiquitous effects of heat on occurrence of human violence." *Psychological Bulletin*, 106, 74.

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

Anderson, Craig A, Kathryn B Anderson, Nancy Dorr, Kristina M DeNeve, and Mindy Flanagan (2000), "Temperature and aggression." In *Advances in Experimental Social Psychology*, volume 32, 63–133, Elsevier.

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

Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S Shapiro (2015), "Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900-2004." *American Economic Review*, 105, 247–51.

Baylis, Patrick (2020), "Temperature and temperament: Evidence from twitter." *Journal of Public Economics*, 184, 104161.

Becker, Gary S (1968), "Crime and punishment: An economic approach." In *The economic dimensions of crime*, 13–68, Springer.

Behrer, A Patrick and Valentin Bolotnyy (forthcoming), "Heat and law enforcement." Policy Research Working Paper Series XXXX, World Bank, Washington, DC.

Blakeslee, David, Ritam Chaurey, Ram Fishman, Deepak Malghan, and Samreen Malik (2018), "In the heat of the moment: economic and non-economic drivers of the weather-crime relationship." *Working Paper*.

Boyanowsky, Ehor (1999), "Violence and aggression in the heat of passion and in cold blood: The ecs-tc syndrome." *international Journal of Law and psychiatry*, 22, 257–271.

Braga, Alfésio Luís Ferreira, Antonella Zanobetti, and Joel Schwartz (2001), "The time course of weather-related deaths." *Epidemiology*, 12, 662–667.

Braga, Anthony A, David M Hureau, and Andrew V Papachristos (2011), "The relevance of micro places to citywide robbery trends: A longitudinal analysis of robbery incidents at street corners and block faces in boston." *Journal of Research in Crime and Delinquency*, 48, 7–32.

Bruederle, Anna, Jörg Peters, and Gareth Roberts (2017), "Weather and crime in south africa."

Burke, Marshall and Kyle Emerick (2016), "Adaptation to climate change: Evidence from us agriculture." *American Economic Journal: Economic Policy*, 8, 106–40.

Burke, Marshall, Sam Heft-Neal, Jessica Li, Anne Driscoll, Patrick Baylis, Matthieu Stigler, Joakim A Weill, Jennifer A Burney, Jeff Wen, Marissa L Childs, et al. (2022), "Exposures and behavioural responses to wildfire smoke." *Nature human behaviour*, 6, 1351–1361.

Card, David and Gordon B Dahl (2011), "Family violence and football: The effect of unexpected emotional cues on violent behavior." *The Quarterly Journal of Economics*, 126, 103–143.

Carleton, Tamma A (2017), "Crop-damaging temperatures increase suicide rates in india." *Proceedings of the National Academy of Sciences*, 114, 8746–8751.

Carleton, Tamma A, Amir Jina, Michael T Delgado, Michael Greenstone, Trevor Houser, Solomon M Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan B Nath, et al. (2020), "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits." Technical report, National Bureau of Economic Research.

Chakraborty, T, A Hsu, D Manya, and G Sheriff (2019), "Disproportionately higher exposure to urban heat in lower-income neighborhoods: A multi-city perspective." *Environmental Research Letters*, 14, 105003.

Cheema, Amar and Vanessa M Patrick (2012), "Influence of warm versus cool temperatures on consumer choice: A resource depletion account." *Journal of Marketing Research*, 49, 984–995.

Cohen, Francois, Fidel Gonzalez, et al. (2018), "Understanding interpersonal violence: the impact of temperatures in mexico." Technical report, Grantham Research Institute on Climate Change and the Environment.

Colmer, Jonathan and Jennifer L Doleac (2022), "Access to guns in the heat of the moment: More restrictive gun laws mitigate the effect of temperature on violence." *Available at SSRN 4195573*.

Correia, Sergio, Paulo Guimarães, and Thomas Zylkin (2019), "Ppmlhdfe: Fast poisson estimation with high-dimensional fixed effects." *arXiv preprint arXiv:1903.01690*.

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

Denissen, Jaap JA, Ligaya Butalid, Lars Penke, and Marcel AG Van Aken (2008), "The effects of weather on daily mood: a multilevel approach." *Emotion*, 8, 662.

Department of Public Safety, Texas (2019), "Seventeenth report examining reporting compliance to the texas computerized criminal history system." Technical report.

Donohue, John J, Samuel V Cai, Matthew V Bondy, and Philip J Cook (2022), "More guns, more unintended consequences: The effects of right-to-carry on criminal behavior and policing in us cities." Working Paper 30190, National Bureau of Economic Research, URL `http://www.nber.org/papers/w30190`.

Fang, Lei, David Peter Wyon, Geo Clausen, and Povl Ole Fanger (2004), "Impact of indoor air temperature and humidity in an office on perceived air quality, sbs symptoms and performance." *Indoor air*, 14, 74–81.

Fesselmeyer, Eric (2019), "The impact of temperature on labor quality: Umpire accuracy in major league baseball." *Available at SSRN 3421241*.

Fletcher, Jason M and Barbara Wolfe (2016), "The importance of family income in the formation and evolution of non-cognitive skills in childhood." *Economics of education review*, 54, 143–154.

Galster, George and Patrick Sharkey (2017), "Spatial foundations of inequality: A conceptual model and empirical overview." *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 3, 1–33.

Garg, Teevrat, Gordon C McCord, and Aleister Montfort (2020), "Can social protection reduce environmental damages?"

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

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

Hausman, Jerry A, Bronwyn H Hall, and Zvi Griliches (1984), "Econometric models for count data with an application to the patents-r&d relationship." Technical Report 17, National Bureau of Economic Research Cambridge.

Heilmann, Kilian and Matthew E Kahn (2019), "The urban crime and heat gradient in high and low poverty areas." Technical report, National Bureau of Economic Research.

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

Heutel, Garth, Nolan H Miller, and David Molitor (2021), "Adaptation and the mortality effects of temperature across us climate regions." *Review of Economics and Statistics*, 103, 740–753.

Hirshleifer, David and Tyler Shumway (2003), "Good day sunshine: Stock returns and the weather." *The Journal of Finance*, 58, 1009–1032.

Hsiang, Solomon (2016), "Climate econometrics." *Annual Review of Resource Economics*, 8, 43–75.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, DJ Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, et al. (2017a), "Estimating economic damage from climate change in the united states." *Science*, 356, 1362–1369.

Hsiang, Solomon, Paulina Oliva, and Reed Walker (2017b), "The distribution of environmental damages." URL `http://www.nber.org/papers/w23882`.

IPCC (2014), "Ipcc fifth assessment report—synthesis report."

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

Keltner, Dacher, Phoebe C Ellsworth, and Kari Edwards (1993), "Beyond simple pessimism: Effects of sadness and anger on social perception." *Journal of Personality and Social Psychology*, 64, 740.

Kenrick, Douglas T and Steven W MacFarlane (1986), "Ambient temperature and horn honking: A field study of the heat/aggression relationship." *Environment and Behavior*, 18, 179–191.

Kim, Jiyoon, Ajin Lee, and Maya Rossin-Slater (2021), "What to expect when it gets hotter: The impacts of prenatal exposure to extreme temperature on maternal health." *American Journal of Health Economics*, 7, 000–000.

Larrick, Richard P, Thomas A Timmerman, Andrew M Carton, and Jason Abrevaya (2011), "Temper, temperature, and temptation: Heat-related retaliation in baseball." *Psychological Science*, 22, 423–428.

Lerner, Jennifer S, Ye Li, Piercarlo Valdesolo, and Karim S Kassam (2015), "Emotion and decision making." *Annual Review of Psychology*, 66.

Levy, Brian L, Nolan E Phillips, and Robert J Sampson (2020), "Triple disadvantage: Neighborhood networks of everyday urban mobility and violence in us cities." *American Sociological Review*, 85, 925–956.

McEwen, Bruce S and Robert M Sapolsky (1995), "Stress and cognitive function." *Current Opinion in Neurobiology*, 5, 205–216.

Mukherjee, Anita and Nicholas J Sanders (2021), "The causal effect of heat on violence: Social implications of unmitigated heat among the incarcerated." Working Paper 28987, National Bureau of Economic Research, URL `http://www.nber.org/papers/w28987`.

Nichols, Austin et al. (2010), "Regression for nonnegative skewed dependent variables." In *BOS10 Stata Conference*, volume 2, 15–16, Stata Users Group.

Obradovich, Nick, Dustin Tingley, and Iyad Rahwan (2018), "Effects of environmental stressors on daily governance." *Proceedings of the National Academy of Sciences*, 115, 8710–8715.

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

Park, R Jisung, A Patrick Behrer, and Joshua Goodman (2020a), "Learning is inhibited by heat exposure, both internationally and within the united states." *Nature human behaviour*, 1–9.

Park, R Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith (2020b), "Heat and learning." *American Economic Journal: Economic Policy*, 12, 306–39.

Peng, Wei, Gokul Iyer, Valentina Bosetti, Vaibhav Chaturvedi, James Edmonds, Allen A Fawcett, Stéphane Hallegatte, David G Victor, Detlef van Vuuren, and John Weyant (2021), "Climate policy models need to get real about people—here's how." *Nature*, 54.

Ranson, Matthew (2014), "Crime, weather, and climate change." *Journal of environmental economics and management*, 67, 274–302.

Rasmussen, DJ, Malte Meinshausen, and Robert E Kopp (2016), "Probability-weighted ensembles of us county-level climate projections for climate risk analysis." *Journal of Applied Meteorology and Climatology*, 55, 2301–2322.

Schwarz, Norbert and Gerald L Clore (1983), "Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states." *Journal of Personality and Social Psychology*, 45, 513.

Seppanen, Olli, William J Fisk, and QH Lei (2006), "Effect of temperature on task performance in office environment." *Lawrence Berkeley National Laboratory*.

Weisburd, David (2015), "The law of crime concentration and the criminology of place." *Criminology*, 53, 133–157.

Weisheit, Ralph A, David N Falcone, and L Edward Wells (1994), *Rural crime and rural policing*, volume 2. US Department of Justice, Office of Justice Programs, National Institute of . . . .

Wooldridge, Jeffrey M (1999), "Distribution-free estimation of some nonlinear panel data models." *Journal of Econometrics*, 90, 77–97.

Wyon, David P, Inger Wyon, and Fredrik Norin (1996), "Effects of moderate heat stress on driver vigilance in a moving vehicle." *Ergonomics*, 39, 61–75.

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Appendix 1 Non-violent Crime Results

In contrast to our results on individual violent crimes, when we look at individual non-violent crimes we see little impact of heat. This is true for both non-violent property crimes and other non-violent crimes. In Figure A7, we see no evidence of an impact of heat on larceny, burglary, or stolen property charges. We also see no evidence of an increase in drug charges related to marijuana. It appears that heat may actually reduce charges for marijuana possession, perhaps because, just as with cold temperatures, at very high temperatures individuals are less likely to be outside and in possession of marijuana.

There are also a number of crimes in our data that do not fit neatly into violent or non-violent categories. We examine some of these crimes separately and generally find no evidence of an impact of heat (Figure A8). Privacy violations, DUIs, and hit and runs all may increase slightly at temperatures over 90°F, but our estimates are all imprecise.

Appendix 2 Impacts of Heat by Neighborhood Housing Age and Incomes Separately

We find substantial impacts of heat in older, less air conditioned neighborhoods.[23] In Table A15, we compare estimates of the impact of heat on overall crime in block groups where the median house was built prior to 1990 to the impact in block groups where the median house was built after 2000. The results in columns 1 and 2 indicate that an additional day above 90°F - relative to a day in the omitted bin - in block groups with older housing increases crime by approximately 5%. The same day in a block group with new housing slightly increases crime for days above 90°F and less than 100°F, but may reduce crime above 100°F.[24] We observe similar patterns for violent crime, with violent crimes increasing by roughly 400% more in older, relative to newer, neighborhoods on hot days.

The specific pattern of the impacts across neighborhoods within violent and non-violent crimes is notable. First, violent crime increases substantially more due to high temperatures in older neighborhoods - consistent with the hypothesis that they have less air conditioning and consequently the impacts of heat on aggression are more severe. A day above 100°F increases violent crime by 17% in older neighborhoods but by only (an insignificant) 6% in newer neighborhoods. Second, while heat does not appear to increase non-violent arrests in either type of neighborhood, it does appear to substantially reduce non-violent crime in newer, presumably more air conditioned, neighborhoods. This is consistent with individuals

[23]In Table A6, we show the impacts of heat in areas with above and below median levels of central air conditioning according to CoreLogic data. Impacts in the areas with above median levels of central AC are 50%+ smaller than in areas with below median levels of central AC. We do not use this as our primary approach because the CoreLogic data do not cover every block group in Texas.

[24]One reason crime might go down at high temperatures in more air conditioned neighborhoods is that overall activity declines when one can stay inside in a cool room on a hot day. Thus, there is less crime due to fewer overall interaction.

in areas with more air conditioning remaining home more during extremely hot periods and seeing a resulting decline in non-violent arrests due to a decline in activity outside of the home.[25]

We turn next to how the impact of heat on crime varies across high and low income neighborhoods.[26]

In Table A16, we show that the impact of heat on crimes is highest in the neighborhoods in the lowest quartile of income and declines roughly monotonically as one moves up the income distribution. Columns 1-4 show the impact of heat on all crimes. In block groups in the lowest income quartile, a day above 90°F increases crime by 7-8%. This falls to 4-5% in the second quartile and 3-4% in the third. Our estimates suggest that heat has no impact on crimes in block groups in the richest quartile.

A look at the impact of heat on violent and non-violent arrests separately (see Table A16, columns 5-12) indicates that heat increases violent crimes across all income quartiles. The effect in the highest income quartile is roughly half of the effect in the lowest, but it is still economically and statistically significant (11% vs. 19% for an additional day above 90°F). Because our data report the address of the arrestee, we can be reasonably certain that these are crimes committed by individuals who themselves live in the high income neighborhoods.[27] Heat does not appear to meaningfully increase non-violent crime in any but the lowest income quartile, where the increase is roughly 4.5% for an additional day above 90°F. While income may reduce the negative impacts of heat on crime, it does not eliminate them – high temperatures result in substantial increases in violent crime even in high income areas. This lends further support to the hypothesis that heat is acting via a universal psychological and cognitive mechanism that can be mitigated, but not eliminated, by investment in (expensive) adaptive technology.[28]

[25]Domestic assaults are coded in our data as violent crimes.

[26]Using CoreLogic data, we document that block groups with median incomes that are below the sample median are 8% less likely to have any air conditioning relative to those above the median. Below median income block groups are 11% less likely to have central air conditioning, and conditional on having air conditioning but not having central air, they are 32% more likely to have a window unit.

[27]This rules out one hypothesis by which the increase in crimes in these neighborhoods is due to crimes committed by poor individuals who travel to wealthy areas and commit crimes.

[28]We can also measure the impact of heat in high and low poverty neighborhoods as an alternative to using income quartiles. We find very similar results in Table A9. Heat leads to large increases in violent crimes in both high and low poverty neighborhoods with effects in high poverty neighborhoods that are 50-80% higher than those in low poverty neighborhoods. Non-violent crimes in high poverty neighborhoods are also increased by high temperatures, but by a substantially smaller amount. Violent crimes in high poverty neighborhoods increase by approximately 17% for an additional day above 90°F, while non-violent crimes increase by 2-5% for the same day. Consistent with our previous results, non-violent crimes do not appear to increase significantly on hot days in low poverty neighborhoods and may decline on the hottest days.

Appendix 3 Impacts of Heat: Rural vs. Urban Areas, High vs. Low Violence Neighborhoods, and by Race and Ethnicity

Existing evidence suggests that crime rates are lower in rural areas (Weisheit et al., 1994). Urban areas also experience a longer duration temperature shock for a given daily maximum temperature because of the urban heat effect, and these impacts tend to be concentrated in low income neighborhoods (Chakraborty et al., 2019). These findings suggest that a given temperature shock may increase crime more in urban areas than rural ones as the severity of shock may be higher and base rates of crime may be higher.

We test this hypothesis by dividing block groups into rural or urban based on the share of the population in the block group that is classified as rural or urban by the Census. We consider urban those block groups with more than 80% of the population classified as urban.[29] We then examine how crime in urban and rural areas responds to a given temperature shock.

We find no evidence of differences in the response of crime to high temperatures across rural and urban areas. Figure A16 shows that crime responds to high temperatures at essentially the same rate in urban and rural areas across the full set of temperature bins. One reason for this may be that our data does not indicate a substantial gradient in temperatures across the urban and rural block groups in our sample. One hypothesis for higher impacts in urban areas relative to rural ones for a given temperature shock is that the temperature shock manifests as higher temperatures in an urban area because of the urban heat effect. While the urban heat effect certainly exists and there is substantial variation across neighborhoods in some cities, in our sample urban areas are on average only $0.5°$ hotter than rural districts on a given day.

Relatedly, we ask whether heat has a larger impact on violent crimes in areas that experience more violence. There is a robust literature that finds crime is highly spatially concentrated, in many cases with large majorities of crimes occurring on a tiny fraction of street corners or city blocks (Weisburd, 2015; Braga et al., 2001, 2011; Galster and Sharkey, 2017). Given this concentration of crime, if heat were driving increases primarily among those who were already pre-disposed to commit crime, as opposed to having a more general effect, one might expect heat to have larger impacts in areas with more existing crime. We do not find any evidence for this hypothesis - the impact of heat on violent crime is the same in block groups that are in the top quartile of the violence distribution and those that are in the bottom quartile (Table A17). The consistency in the impacts across neighborhoods with different levels of existing crime also suggests that our results are not driven by unequal changes in police activity. Arrests increase equally in percentage terms in areas with high and low existing levels of violence, which suggests that police are not concentrating their efforts on hotter days in more crime prone areas.

Our data on arrests include information about the race and ethnicity of the defendants. This allows us to examine whether heat has differential impacts on arrests across different racial and ethnic groups. We focus on the two most represented racial groups in our data - White (non-Hispanic) defendants and Black defendants - as well as Hispanic defendants of

[29] The resulting urban and rural block groups are mapped in Figure A15.

any race. We do not find evidence that suggests heat increases arrests differentially for any of these groups.

Figure A10 shows how temperature impacts total crimes, violent crimes, and non-violent crimes for each of these three groups. There is no meaningful difference in either total crimes or violent crimes at any point in the temperature distribution by race and ethnicity. Non-violent crimes may decline for White and Black defendants at especially high temperatures, while we estimate a null effect for Hispanic defendants at these temperatures. The differences in point estimates, however, are not statistically distinguishable.

Finally, we examine whether the impact of heat on arrests is concentrated in majority minority neighborhoods. O'Flaherty and Sethi (2010) finds street crime disproportionately occurs in minority, specifically Black, neighborhoods despite perpetrators not being disproportionately Black. Other work has suggested that these neighborhoods are disproportionately exposed to criminal activity and that the difference in exposure between disadvantaged neighborhoods and others has grown over time. Examining the impact of heat across block groups where the majority is White, Black, or Hispanic, we find no difference in the effect of heat (Table A10).[30]

Appendix 4 Calculation of Future Damages

We estimate the impact of future climate change by starting with the temperature projections created by Rasmussen et al. (2016) and made available as part of the replication data for Hsiang et al. (2017a). Their data provides projections for the number of annual days the maximum temperature is in each 1°C bins from -40°C to 59°C for every county in the continental United States from 1981 to 2100. They provide projections under each of the RCP scenarios from a suite of GCM models for each scenario. We use data from RCP2.6, RCP6.0, and RCP8.5. Their data include output from 29, 28, and 44 GCM models for each scenario, respectively.

Using these data, we calculate the projected number of days that each county in Texas will experience a maximum temperature in the following bins: < 40°F, ten degree bins to 90°F, and > 90°F in each year from 2000 to 2050. We calculate these days for every model for which they provide output for the RCP2.6, RCP6.0, and RCP8.5 scenarios. We use the average in each bin from 2000 to 2010 as our base and then calculate the change in the number of these days from the base for each year from 2020 to 2050. This gives us a balanced panel of the change in days in every bin by county and year for every county in Texas from 2020 to 2050.

We estimate the impact that these projected future temperatures will have on arrests under a range of adaptation scenarios. First, a base scenario that assumes no adaptation and that the coefficients we estimate pooling across our entire sample remain stable into the future. Second, a scenario in which income predicts adaptation. Third, a scenario in which the median age of the housing stock predicts adaptation, and finally a scenario in which income and housing age jointly predict adaptation. In all scenarios, we calculate income

[30] We examine whether county-level temperature shocks manifest differently in block groups with a different majority race or ethnicity. We find no meaningful difference. The largest difference is 0.5° between Hispanic-majority and Black-majority block groups.

and housing age at the block group level and estimate variants of the primary regressions presented in the paper using 10° bins, with the highest bin at $> 90°$F to increase precision of our estimates. As in our primary approach, we calculate the number of violent crimes at the block group level and aggregate to the county level within the appropriate (for instance quantiles of the income distribution) bin. For our income based scenarios, we estimate within each income quantile, and for the building age scenarios we estimate in three bins, ≤ 1990, $1990 - 2000$, and ≥ 2000. For the joint scenario, we estimate the marginal impact separately for each building age bin within each income quantile. This gives us a set of marginal estimates for each temperature bin in each scenario ranging from 1 estimate per bin in the base scenario to 12 estimates per bin in the joint income and housing age scenario (for instance income Q1, housing age ≤ 1990 or income Q4, housing age ≥ 2000).

In order to assign block groups to each income quantile in future years we calculate the average median income in each block group from 2014 to 2018. We use this as the base year income. We then extrapolate income forward in time using two different approaches. In the first, we calculate the compound annual growth rate that explains the observed income growth from 2010 to 2018 individually for every block group in our sample. We impose that block groups cannot experience negative growth in median income in the future and so replace any negative growth rates calculated this way with a zero growth rate. We then use these individual growth rates to predict median income in every block group in every year from 2020 to 2050. In the second approach, we assume that each block group experiences a compound annual growth rate equal to that experienced by the United States as a whole from 2002 to 2019 based on data from the U.S. Census. In the second approach, we calculate a growth rate for each block group as a whole as well as for median incomes in Black, White non-Hispanic, and Hispanic households separately. To extrapolate housing ages, we do a similar exercise where we calculate the compound annual growth rate that explains the observed change in each block group individually. Again, we extrapolate using the individual growth rates and using an average of these growth rates applied to every block group. We also impose the restriction that housing cannot get older on average.

We also conduct a "high adaptation" scenario in which we assume that the growth rate in the future will be 10x the observed growth rate. This rate is chosen so that 99+% of block groups reach the highest income quantile and the newest building tercile by 2050.

We assign each block group to income quantiles and building age bins based on the extrapolated value of their median income and median building age in each year from 2020 to 2050. We maintain the same thresholds for the quantiles and bins as we use in our initial estimation of the marginal effects throughout this exercise. As a result, the share of block groups in the wealthiest quantiles and newest building bins increases over time. We calculate future impacts with the following equation:

$$Impact_{byms} = \sum_{k=1}^{7} \text{Marginal Impact}_{iak} \times \left(Days_{cymsk} - \overline{Days_{cmsk,2000-2010}} \right) \tag{2}$$

such that $Impact$ in block group b in year y in model m and RCP scenario s is equal to the sum of the impacts across all k temperature bins. The impact in each bin is calculated as the marginal effect for that temperature bin income quantile i and building age a, as applicable, times the difference in the number of days in that temperature bin in that year in county c in which the block group is located and the average number of days in that temperature bin from 2000 to 2010 in the same county.

We assign each block group the future temperatures of the county that contains it and calculate the damages in each year based on the income quantile and building age bin applicable for that block group in that year. These marginal damages vary depending on whether we are calculating the base scenario, the building age alone, income alone, or the building age and income scenario. We calculate every scenario individually for every model run for every RCP scenario. Our projected damages are then the average of these model outputs within each RCP scenario, with confidence intervals defined by the standard deviation of the impacts across model runs.

Appendix 5 Additional Tables

Table A1: Impact of heat on total crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T >100F	0.047	0.045	0.049	0.044	0.031	0.028	0.052	0.043	0.036
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 95-100F	0.056	0.054	0.056	0.051	0.046	0.045	0.049	0.053	0.049
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 90-95F	0.048	0.048	0.052	0.043	0.048	0.049	0.047	0.047	0.044
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 85-90F	0.045	0.045	0.046	0.039	0.042	0.043	0.045	0.044	0.042
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
T 80-85F	0.042	0.043	0.043	0.039	0.039	0.040	0.041	0.041	0.040
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
T 75-80F	0.019	0.023	0.021	0.021	0.019	0.023	0.025	0.022	0.021
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
T 70-75F	0.025	0.030	0.027	0.030	0.025	0.030	0.029	0.030	0.029
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
T 65-70F	0.018	0.015	0.016	0.013	0.018	0.015	0.015	0.014	0.014
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 55-60F	-0.003	-0.009	-0.004	-0.003	-0.002	-0.008	-0.008	-0.008	-0.008
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
T 50-55F	-0.043	-0.036	-0.042	-0.020	-0.044	-0.037	-0.036	-0.036	-0.035
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 45-50F	-0.047	-0.036	-0.042	-0.016	-0.048	-0.036	-0.036	-0.037	-0.036
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 40-45F	-0.073	-0.066	-0.069	-0.048	-0.075	-0.066	-0.067	-0.065	-0.064
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T below 40F	-0.136	-0.148	-0.136	-0.137	-0.138	-0.149	-0.147	-0.147	-0.145
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	742,188	742,188	742,188	742,188	742,188	742,188	739,630	741,934	741,934
Fixed Effects:									
County	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Month	Yes	Yes	Yes	Yes			Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes				Yes	Yes
DOW		Yes		Yes		Yes	Yes	Yes	Yes
Weekend			Yes						
DOY				Yes					
Month × Year					Yes	Yes			
County × Year							Yes		
Additional controls:									
Dew point								Yes	Yes
Vapor pressure deficit									Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parenthesis. All regressions are weighted by the total population in each county-year. All regressions include the full set of precipitation bins. 100× the coefficient estimates indicate the percent change on days in each bin relative to a day in the omitted 60-65°F bin. Dew point is the average dew point temperature reported in PRISM and minimum vapor pressure deficit is the minimum vapor pressure deficit reported on the day in the PRISM data.

Table A2: Impact of heat on violent crime - weekday vs. weekend

	Weekdays	Weekend
T above 100F	0.162	0.157
	(0.02)	(0.03)
T 95-100F	0.132	0.146
	(0.02)	(0.02)
T 90-95F	0.128	0.128
	(0.02)	(0.02)
T 85-90F	0.100	0.141
	(0.01)	(0.02)
T 80-85F	0.093	0.121
	(0.01)	(0.01)
T 75-80F	0.061	0.066
	(0.01)	(0.02)
T 70-75F	0.059	0.074
	(0.01)	(0.02)
T 65-70F	0.049	0.036
	(0.02)	(0.02)
T 55-60F	0.027	-0.039
	(0.01)	(0.02)
T 50-55F	-0.003	-0.009
	(0.02)	(0.02)
T 45-50F	0.009	-0.104
	(0.02)	(0.02)
T 40-45F	-0.022	-0.041
	(0.04)	(0.03)
T below 40F	-0.093	-0.201
	(0.01)	(0.04)
N	527,758	211,508
Fixed Effects:		
County	Yes	Yes
Month	Yes	Yes
Year	Yes	Yes
DOW	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parenthesis. All regressions are weighted by the total population in each county-year. All regressions include the full set of precipitation bins. 100× the coefficient estimates indicate the percent change on days in each bin relative to a day in the omitted 60-65°F bin.

Table A3: Impact of heat on total crime, date of offense

	(1)	(2)	(3)	(4)	(5)	(6)
T above 100F	0.059	0.060	0.036	0.036	0.056	0.042
	(0.016)	(0.017)	(0.018)	(0.018)	(0.021)	(0.015)
T 95-100F	0.055	0.055	0.038	0.040	0.051	0.044
	(0.014)	(0.011)	(0.009)	(0.009)	(0.011)	(0.009)
T 90-95F	0.045	0.049	0.040	0.044	0.045	0.040
	(0.013)	(0.012)	(0.012)	(0.011)	(0.012)	(0.010)
T 85-90F	0.051	0.053	0.045	0.048	0.049	0.045
	(0.009)	(0.009)	(0.009)	(0.008)	(0.012)	(0.009)
T 80-85F	0.050	0.052	0.043	0.045	0.049	0.046
	(0.007)	(0.006)	(0.005)	(0.004)	(0.008)	(0.006)
T 75-80F	0.022	0.029	0.020	0.026	0.026	0.024
	(0.005)	(0.005)	(0.005)	(0.004)	(0.007)	(0.006)
T 70-75F	0.028	0.035	0.027	0.033	0.033	0.032
	(0.005)	(0.006)	(0.004)	(0.004)	(0.006)	(0.005)
T 65-70F	0.020	0.015	0.020	0.014	0.014	0.014
	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
T 55-60F	0.003	-0.003	0.003	-0.002	-0.002	-0.001
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
T 50-55F	-0.041	-0.031	-0.043	-0.033	-0.031	-0.030
	(0.014)	(0.010)	(0.013)	(0.010)	(0.009)	(0.009)
T 45-50F	-0.047	-0.030	-0.049	-0.031	-0.032	-0.030
	(0.017)	(0.015)	(0.018)	(0.016)	(0.013)	(0.012)
T 40-45F	-0.073	-0.063	-0.075	-0.063	-0.062	-0.060
	(0.007)	(0.007)	(0.009)	(0.009)	(0.005)	(0.006)
T below 40F	-0.130	-0.144	-0.134	-0.147	-0.141	-0.137
	(0.021)	(0.012)	(0.021)	(0.011)	(0.014)	(0.015)
N	742,188	742,188	742,188	742,188	741,934	741,934
Fixed Effects:						
County	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes			Yes	Yes
Year	Yes	Yes			Yes	Yes
DOW		Yes		Yes	Yes	Yes
Month × Year			Yes	Yes		
Additional controls:						
Dew point					Yes	Yes
Vapor pressure deficit						Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. All regressions include the full set of precipitation bins. 100× the coefficient estimate indicates the percent change on days in each bin relative to a day in the omitted 60-65°F bin. Instead of day of arrest, here we match day of offense with temperature data. Dew point is the average dew point temperature reported in PRISM and minimum vapor pressure deficit is the minimum vapor pressure deficit reported on the day in the PRISM data.

Table A4: Impact of heat on total crime, lags

	No lag	1 lag	2 lags	3 lags	4 lags	5 lags
T above 100F	0.050	0.068	0.066	0.064	0.064	0.062
	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
T 95-100F	0.059	0.071	0.071	0.069	0.070	0.069
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T 90-95F	0.052	0.068	0.069	0.068	0.068	0.068
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
T 85-90F	0.048	0.062	0.062	0.062	0.061	0.060
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
T 80-85F	0.045	0.059	0.060	0.059	0.059	0.059
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
N	740,410	740,410	740,410	740,410	740,410	740,410
$\Sigma_{i=1}^{5} lag_i$,T above 100F		0.032	0.048	0.061	0.069	0.082
		(0.017)	(0.020)	(0.024)	(0.023)	(0.023)
$\Sigma_{i=1}^{5} lag_i$,T 95 to 100F		0.044	0.056	0.072	0.080	0.085
		(0.010)	(0.012)	(0.013)	(0.014)	(0.015)
$\Sigma_{i=1}^{5} lag_i$,T 90 to 95F		0.034	0.041	0.048	0.051	0.054
		(0.010)	(0.014)	(0.013)	(0.017)	(0.016)
$\Sigma_{i=1}^{5} lag_i$,T 85 to 90F		0.035	0.047	0.060	0.071	0.081
		(0.010)	(0.014)	(0.013)	(0.015)	(0.017)
$\Sigma_{i=1}^{5} lag_i$,T 80 to 85F		0.029	0.039	0.046	0.060	0.068
		(0.010)	(0.012)	(0.011)	(0.010)	(0.011)
Fixed Effects:						
County	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parenthesis. All regressions are weighted by the total population in each county-year. All regressions include the full set of precipitation bins. 100× the coefficient estimates indicate the percent change on days in each bin relative to a day in the omitted 60-65°F bin. In each column we include the temperature on the day one additional lag prior to the day of arrest.

Table A5: Impact of heat on violent crime, leads

	1 lead	2 leads	3 leads
T above 100F	-0.014	0.013	0.022
	(0.021)	(0.020)	(0.017)
T 95-100F	-0.028	-0.005	0.006
	(0.012)	(0.012)	(0.011)
T 90-95F	-0.018	-0.001	0.000
	(0.019)	(0.008)	(0.006)
T 85-90F	-0.009	0.009	0.003
	(0.017)	(0.009)	(0.005)
T 80-85F	-0.010	0.011	0.008
	(0.008)	(0.006)	(0.006)
N	741,934	741,680	740,918
Fixed Effects:			
County	Yes	Yes	Yes
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
DOW	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parenthesis. All regressions are weighted by the total population in each county-year. All regressions include the full set of precipitation bins. 100× the coefficient estimates indicate the percent change in arrests in the days following a day in each bin relative to if that day had been in the omitted 60-65°F bin. Leads indicate the number of days after the day of interest that we include in the pooled crime counts. For example, 1 lead indicates that we examine the impact of heat on day *n* on arrests on day *n+1*. In all columns we include controls for temperature and precipitation on the leading days.

Table A6: Impact of heat on crime by AC penetration

	Central air	
Quartile:	Below median	Above median
T above 100F	0.262	0.127
	(0.036)	(0.013)
T 95-100F	0.237	0.090
	(0.043)	(0.010)
T 90-95F	0.203	0.086
	(0.047)	(0.010)
T 85-90F	0.158	0.072
	(0.033)	(0.007)
T 80-85F	0.126	0.072
	(0.034)	(0.012)
T 75-80F	0.108	0.026
	(0.032)	(0.008)
N	146,100	222,072
Outcome mean, T60-65	0.09	0.21
Fixed Effects:		
County	Yes	Yes
Month	Yes	Yes
Year	Yes	Yes
DOW	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimate indicates the percent change on days in each bin relative to the baseline in the omitted bin. AC quartiles indicate the quartile of the block group in which the arrested individual resided based on the share of houses in the block group that Corelogic data indicate have air conditioning. We only include block groups with at least 200 homes in the Corelogic data.

Table A7: Impact of heat on total crimes by income and building age

	1^{st} quartile		2^{nd} quartile		3^{rd} quartile		4^{th} quartile	
	Pre-1990	Post-2000	Pre-1990	Post-2000	Pre-1990	Post-2000	Pre-1990	Post-2000
T above 100F	0.059	-0.190	0.037	0.138	0.035	-0.082	-0.036	-0.037
	(0.010)	(0.051)	(0.014)	(0.066)	(0.015)	(0.036)	(0.022)	(0.030)
T 90-100F	0.057	-0.022	0.055	0.006	0.038	0.004	-0.001	0.036
	(0.008)	(0.060)	(0.010)	(0.014)	(0.016)	(0.017)	(0.020)	(0.028)
T 80-90F	0.048	0.014	0.041	0.021	0.042	-0.011	0.008	0.015
	(0.007)	(0.027)	(0.005)	(0.012)	(0.020)	(0.017)	(0.009)	(0.020)
T 70-80F	0.036	0.010	0.017	-0.016	0.011	0.005	-0.007	0.014
	(0.005)	(0.030)	(0.007)	(0.013)	(0.014)	(0.005)	(0.007)	(0.014)
N	677,904	105,192	721,734	146,100	715,890	198,696	523,038	181,164
Outcome mean, T60-65	0.88	0.02	0.72	0.04	0.53	0.10	0.25	0.19
Fixed Effects:								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimates indicate the percent change on days in each bin relative to the baseline in the omitted bin. Building age refers to the median year of home construction in the block group in which the arrested individual resided at the time of arrest. Income quartiles indicate the quartile of the block group in which the arrested individual resided. We calculate quartiles in each year based on the distribution of median incomes by block group. The first quartile includes the lowest income block groups. Quatrile thresholds vary by year.

Table A8: Impact of heat on non-violent crimes by income and building age

	1^{st} quartile		2^{nd} quartile		3^{rd} quartile		4^{th} quartile	
	Pre-1990	Post-2000	Pre-1990	Post-2000	Pre-1990	Post-2000	Pre-1990	Post-2000
T above 100F	0.042	-0.143	-0.015	0.011	-0.056	-0.100	-0.111	-0.112
	(0.015)	(0.081)	(0.014)	(0.054)	(0.025)	(0.058)	(0.017)	(0.023)
T 90-100F	0.039	-0.018	0.047	-0.058	-0.011	-0.009	-0.029	0.031
	(0.015)	(0.040)	(0.016)	(0.046)	(0.019)	(0.025)	(0.017)	(0.044)
T 80-90F	0.038	-0.013	0.019	0.012	-0.008	-0.025	-0.026	0.002
	(0.014)	(0.034)	(0.010)	(0.041)	(0.021)	(0.023)	(0.018)	(0.016)
T 70-80F	0.022	0.029	0.013	0.004	-0.006	-0.017	-0.033	0.008
	(0.002)	(0.040)	(0.006)	(0.020)	(0.021)	(0.008)	(0.012)	(0.013)
N	677,904	105,192	721,734	146,100	707,124	192,852	517,194	181,164
Outcome mean, T60-65	0.39	0.01	0.35	0.02	0.27	0.05	0.13	0.10
Fixed Effects:								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimates indicate the percent change on days in each bin relative to the baseline in the omitted bin. Building age refers to the median year (Pre-1990 or Post-2000) of home construction in the block group in which the arrested individual resided at the time of arrest. Income quartiles indicate the quartile of the block group in which the arrested individual resided. We calculate quartiles each year based on the distribution of median incomes by block group. The first quartile includes the lowest income block groups. Quartile thresholds vary by year.

Table A9: Impact of heat on crimes by poverty rate

	Violent, high poverty	Non-violent, high poverty	Violent, low poverty	Non-violent, low poverty
T above 100F	0.189	0.023	0.126	-0.051
	(0.026)	(0.012)	(0.010)	(0.013)
T 95-100F	0.158	0.052	0.106	-0.009
	(0.030)	(0.014)	(0.009)	(0.008)
T 90-95F	0.162	0.039	0.090	-0.004
	(0.026)	(0.014)	(0.011)	(0.011)
T 85-90F	0.130	0.033	0.089	-0.015
	(0.017)	(0.014)	(0.017)	(0.009)
T 80-85F	0.111	0.033	0.084	-0.004
	(0.026)	(0.011)	(0.015)	(0.007)
T 75-80F	0.060	0.014	0.051	-0.010
	(0.016)	(0.008)	(0.015)	(0.006)
N	710,046	715,890	736,344	742,188
Outcome mean, T60-65	0.26	0.26	0.26	0.89
Fixed Effects:				
County	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimates indicate the percent change on days in each bin relative to the baseline in the omitted bin. High and low refer to the poverty level in the block group in which the arrested individual lives. High poverty block groups are those where the percentage of households below the poverty rate is above the median in our sample. Low poverty block groups are those where the percentage of households below the poverty rate is below the median.

Table A10: Impact of heat on crime by neighborhood majority race and ethnicity

	White			Black			Hispanic		
	All	Violent	Non-violent	All	Violent	Non-violent	All	Violent	Non-violent
T above 100F	0.045	0.161	-0.017	0.052	0.181	-0.016	0.045	0.157	-0.015
	(0.008)	(0.018)	(0.011)	(0.007)	(0.021)	(0.009)	(0.009)	(0.019)	(0.012)
T 95-100F	0.055	0.134	0.019	0.056	0.146	0.019	0.056	0.134	0.022
	(0.007)	(0.019)	(0.008)	(0.006)	(0.020)	(0.008)	(0.007)	(0.019)	(0.009)
T 90-95F	0.049	0.129	0.015	0.047	0.137	0.012	0.050	0.129	0.018
	(0.009)	(0.019)	(0.011)	(0.009)	(0.021)	(0.011)	(0.010)	(0.019)	(0.012)
T 85-90F	0.046	0.111	0.007	0.046	0.116	0.007	0.047	0.111	0.009
	(0.005)	(0.015)	(0.003)	(0.006)	(0.015)	(0.004)	(0.006)	(0.015)	(0.004)
T 80-85F	0.043	0.099	0.013	0.043	0.105	0.012	0.044	0.099	0.015
	(0.004)	(0.014)	(0.002)	(0.004)	(0.016)	(0.003)	(0.005)	(0.014)	(0.003)
T 75-80F	0.024	0.056	0.000	0.020	0.057	-0.004	0.024	0.057	0.001
	(0.003)	(0.014)	(0.002)	(0.002)	(0.015)	(0.002)	(0.003)	(0.014)	(0.003)
N	742,188	739,266	742,188	721,734	715,890	718,812	742,188	739,266	742,188
Outcome mean, T60-65	2.29	0.44	0.44		0.34	2.29	2.90	0.44	2.90
Fixed Effects:									
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Outcomes measure the change in crimes that occur in block groups in which the race or ethnic group identified at the top of the column constitutes a majority of the block group population. White refers to non-Hispanic White individuals. Hispanic refers to Hispanic individuals of any race. Black refers to Black individuals of any ethnicity. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. All regressions include the full set of precipitation bins and temperature bins. 100× the coefficient estimates indicate the percent change on days in each bin relative to a day in the omitted 60-65°F bin.

Table A11: Specific charges grouped as "narrow gun charges"

Charge
PROH WEAPON
UNL CARRYING WEAPON
UNL CARRYING WEAPON PROHIBITED PLACES
DISCHARGE FIREARM LAKE LAVON COLLIN CO
DEADLY CONDUCT DISCHARGE FIREARM
DISCHARGE FIREARM IN CERTAIN MUNICIPALITIES
MAKE FIREARM ACCESSIBLE TO CHILD DEATH/SBI

Notes: List of charges from the Texas AON database that we categorize as "narrow gun charges" for the purpose of evaluating whether the passage of the law permitting handguns to be carried openly in 2016 leads to an increase in the sensitivity of these arrests to ambient temperature.

Table A12: Impact of heat on crime by past heat exposure

	Violent crime				Non-violent crime			
Quartile:	1^{st}	2^{nd}	3^{rd}	4^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}
T above 100F	0.104	0.174	0.163	0.125	-0.021	-0.047	-0.009	-0.010
	(0.011)	(0.034)	(0.017)	(0.037)	(0.009)	(0.013)	(0.013)	(0.024)
T 95-100F	0.120	0.178	0.164	0.108	0.022	-0.017	0.011	0.009
	(0.006)	(0.019)	(0.016)	(0.056)	(0.003)	(0.011)	(0.017)	(0.017)
T 90-95F	0.120	0.121	0.170	0.103	0.035	-0.011	-0.001	-0.005
	(0.006)	(0.032)	(0.029)	(0.033)	(0.003)	(0.013)	(0.017)	(0.010)
T 85-90F	0.111	0.121	0.125	0.092	0.013	-0.016	0.010	-0.006
	(0.005)	(0.028)	(0.020)	(0.040)	(0.002)	(0.010)	(0.008)	(0.004)
T 80-85F	0.101	0.076	0.101	0.104	0.012	-0.028	0.024	0.006
	(0.002)	(0.030)	(0.022)	(0.031)	(0.002)	(0.012)	(0.004)	(0.011)
T 75-80F	0.055	0.052	0.086	0.060	0.004	-0.027	0.010	-0.003
	(0.002)	(0.034)	(0.019)	(0.025)	(0.002)	(0.028)	(0.008)	(0.006)
N	137,334	417,846	327,264	333,108	140,256	420,768	333,108	336,030
Outcome mean, T60-65	0.14	0.12	0.16	0.15	0.43	0.34	0.42	0.38
Fixed Effects:								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimate indicates the percent change on days in each bin relative to the baseline in the omitted bin. Temperature quartiles indicate the quartile of the block group in which the arrested individual resided based on the average number of high temperature days (100°F+) experienced by the block group across our sample. The first quartile includes the least exposed block groups.

TABLE A13: Future heat exposure

	RCP2.6				RCP6.0				RCP8.5			
	2000-2010	2025-2030	2035-2040	2045-2050	2000-2010	2025-2030	2035-2040	2045-2050	2000-2010	2025-2030	2035-2040	2045-2050
Future days $> 100°$**F**												
Race & Ethnicity												
Black residents	81.50	71.86	90.01	87.12	70.42	68.30	75.88	74.09	73.61	78.31	122.60	110.59
Hispanic residents	79.86	72.90	90.20	86.32	66.99	70.55	83.67	74.38	69.72	76.00	113.54	111.36
White residents	76.55	79.87	90.90	88.39	69.48	73.97	86.81	81.38	69.73	78.73	107.85	111.92
Median income												
Below median	78.96	78.55	90.92	87.83	68.84	74.30	86.07	81.59	69.23	77.73	108.99	106.54
Above median	78.42	77.86	90.39	88.19	70.10	72.83	84.69	79.90	70.84	78.24	112.23	113.37
Housing age												
Pre-1990	79.74	77.80	90.65	87.29	69.63	73.28	84.47	79.29	70.45	77.98	112.70	107.85
Post-2000	76.49	78.08	91.96	89.75	69.88	72.52	87.64	84.67	71.05	76.62	104.77	116.96

NOTES: Averages by race and ethnicity report the block group average exposure weighted by the population in each category in that block group. "White residents" reports the exposure of White, non-Hispanic residents. "Hispanic" reports exposure of Hispanic residents of any race. We measure quartiles of previous exposure to temperature based on the quartile of the number of days $> 100°$F.

Table A14: 2050 quantile summary statistics

	Base scenario				10x adaptation scenario			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Income quantile	2.97	1.04	1	4	4.00	0.05	1	4
Income quantile, Black	2.46	1.25	1	4	3.90	0.47	1	4
Income quantile, White	3.14	1.00	1	4	4.00	0.04	2	4
Income quantile, Hispanic	2.86	1.09	1	4	4.00	0.06	2	4
Building age bin	1.94	0.86	1	3	3.00	0.00	3	3

Notes: Statistics are calculated across all block groups in 2050 based on our projections of income and median building age.

Table A15: Impact of heat on arrests by building age

	Total crime		Violent crime		Non-violent crime	
	Pre-1990	Post-2000	Pre-1990	Post-2000	Pre-1990	Post-2000
T above 100F	0.052	-0.025	0.171	0.055	-0.008	-0.089
	(0.007)	(0.017)	(0.016)	(0.034)	(0.009)	(0.020)
T 95-100F	0.055	0.048	0.139	0.086	0.018	0.021
	(0.005)	(0.019)	(0.017)	(0.044)	(0.008)	(0.028)
T 90-95F	0.053	0.017	0.139	0.044	0.019	-0.006
	(0.009)	(0.016)	(0.017)	(0.025)	(0.011)	(0.021)
T 85-90F	0.050	0.015	0.123	0.020	0.010	-0.014
	(0.004)	(0.015)	(0.011)	(0.036)	(0.004)	(0.012)
T 80-85F	0.046	0.016	0.108	0.028	0.016	-0.004
	(0.004)	(0.010)	(0.011)	(0.029)	(0.002)	(0.009)
T 75-80F	0.024	0.015	0.063	0.008	0.001	-0.001
	(0.003)	(0.005)	(0.013)	(0.024)	(0.003)	(0.008)
N	742,188	277,590	739,266	242,526	742,188	271,746
Outcome mean, T60-65	2.88	0.35	0.46	0.05	1.40	0.19
Fixed Effects:						
County	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimate indicates the percent change on days in each bin relative to the baseline in the omitted bin. Building age refers to the median year (Pre-1990 or Post-2000) of home construction in the block group in which the arrested individual resided at the time of arrest.

Table A16: Impact of heat on arrests by income quartile

	Total crime				Violent crime				Non-violent crime			
Quartiles:	1^{st}	2^{nd}	3^{rd}	4^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}
T above 100F	0.082	0.047	0.036	-0.007	0.191	0.196	0.097	0.114	0.045	-0.024	-0.033	-0.078
	(0.012)	(0.017)	(0.011)	(0.019)	(0.027)	(0.041)	(0.023)	(0.021)	(0.014)	(0.017)	(0.023)	(0.024)
T 95-100F	0.088	0.047	0.045	0.021	0.180	0.149	0.097	0.091	0.045	0.027	0.003	-0.013
	(0.009)	(0.011)	(0.005)	(0.012)	(0.024)	(0.038)	(0.014)	(0.022)	(0.013)	(0.011)	(0.008)	(0.019)
T 90-95F	0.075	0.058	0.032	0.021	0.178	0.150	0.075	0.087	0.035	0.036	0.000	-0.016
	(0.008)	(0.013)	(0.008)	(0.016)	(0.024)	(0.030)	(0.014)	(0.019)	(0.010)	(0.018)	(0.011)	(0.021)
T 85-90F	0.072	0.047	0.033	0.020	0.160	0.120	0.061	0.097	0.033	0.015	-0.007	-0.019
	(0.010)	(0.008)	(0.009)	(0.010)	(0.016)	(0.028)	(0.013)	(0.013)	(0.008)	(0.006)	(0.010)	(0.012)
T 80-85F	0.061	0.045	0.041	0.020	0.123	0.109	0.081	0.092	0.042	0.016	0.002	-0.010
	(0.005)	(0.008)	(0.010)	(0.011)	(0.018)	(0.030)	(0.012)	(0.022)	(0.011)	(0.012)	(0.008)	(0.012)
T 75-80F	0.045	0.023	0.016	0.006	0.087	0.059	0.030	0.073	0.021	0.007	-0.004	-0.021
	(0.004)	(0.005)	(0.003)	(0.006)	(0.018)	(0.018)	(0.011)	(0.011)	(0.007)	(0.010)	(0.005)	(0.009)
N	683,748	721,734	715,890	540,570	677,904	721,734	704,202	499,662	683,748	721,734	707,124	534,726
Outcome mean, T60-65	0.98	0.85	0.78	0.60	0.19	0.15	0.13	0.09	0.44	0.41	0.39	0.33
Fixed Effects:												
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimate indicates the percent change on days in each bin relative to the baseline in the omitted bin. Income quartiles indicate the quartile of the block group in which the arrested individual resided. We calculate quartiles each year based on the distribution of median incomes by block group. The first quartile includes the lowest income block groups. Quartile thresholds vary by year.

Table A17: Impact of heat on violent crime by general level of violence

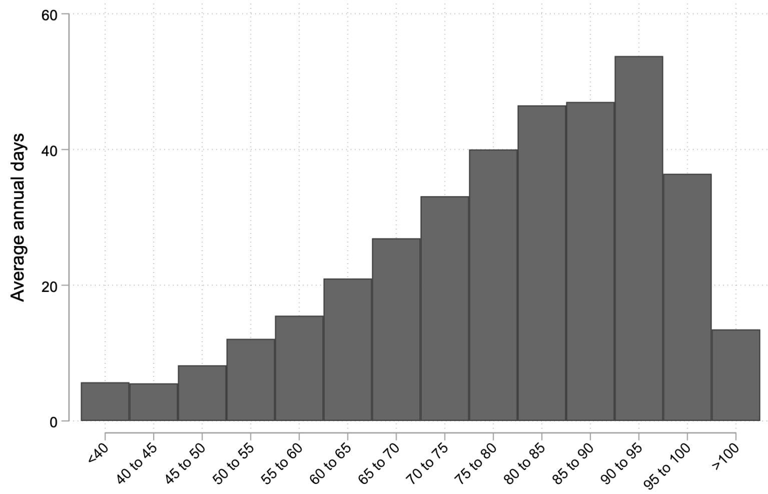
	High violence	Low violence
T above 100F	0.172	0.173
	(0.027)	(0.036)
T 95-100F	0.140	0.207
	(0.025)	(0.020)
T 90-95F	0.141	0.193
	(0.024)	(0.023)
T 85-90F	0.121	0.185
	(0.019)	(0.022)
T 80-85F	0.109	0.127
	(0.016)	(0.038)
T 75-80F	0.074	0.019
	(0.015)	(0.041)
N	601,932	651,606
Outcome mean, T60-65	0.37	0.02
Fixed Effects:		
County	Yes	Yes
Month	Yes	Yes
Year	Yes	Yes
DOW	Yes	Yes

Notes: All columns report the results of a Poisson fixed effects specification. Errors are clustered at the county level and are reported in parentheses. All regressions are weighted by the total population in each county-year. Coefficients for bins below 75°F are suppressed for parsimony, but all regressions include the full set of temperature bins and the full set of precipitation bins. Outcome mean indicates the average number of arrests on days in the omitted bin. 100× the coefficient estimate indicates the percent change on days in each bin relative to the baseline in the omitted bin. To determine "violent" block groups vs. "non-violent" ones, we calculate the daily average number of violent crime arrests across our full sample. Block groups that have a daily average number of violent crime arrests above the sample 75^{th} percentile are considered high violence and those below the 25^{th} percentile are considered low violence.

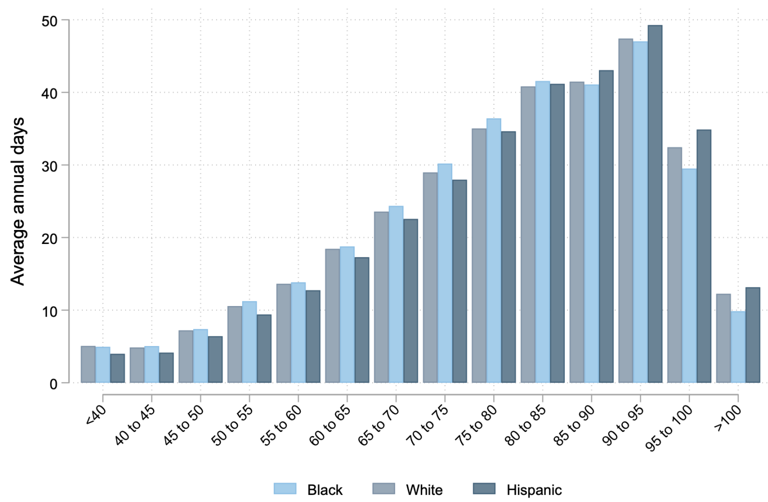
Appendix 6 Additional Figures

Figure A1: Temperature distributions

(a) Full sample



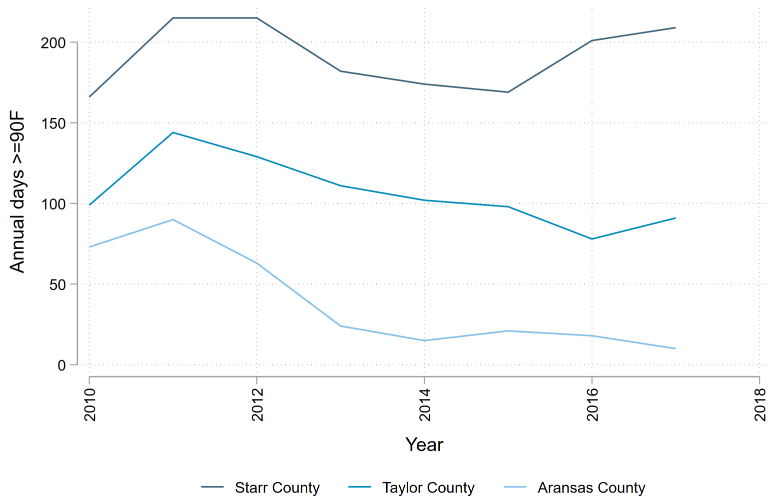
(b) Temperature distribution by race



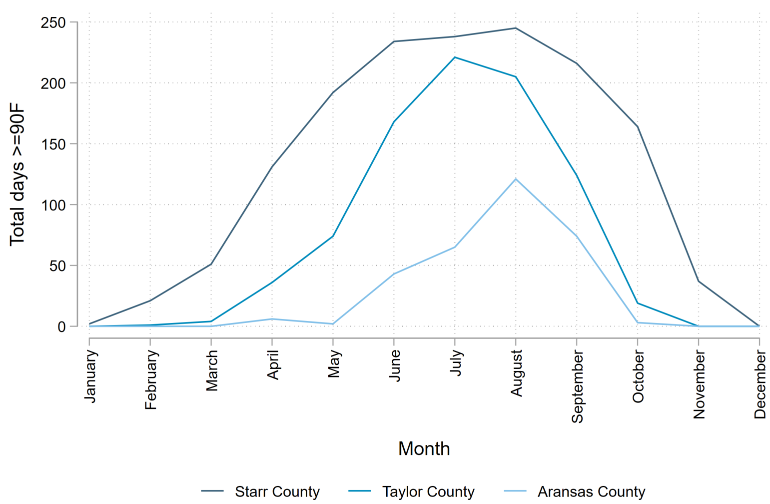
Notes: Panel A plots the distribution of days in each temperature bin averaged across all counties and years in the sample. Panel B reports the same, but shows distributions separately by race and ethnicity.

Figure A2: Hot day distributions

(a) Annual hot days



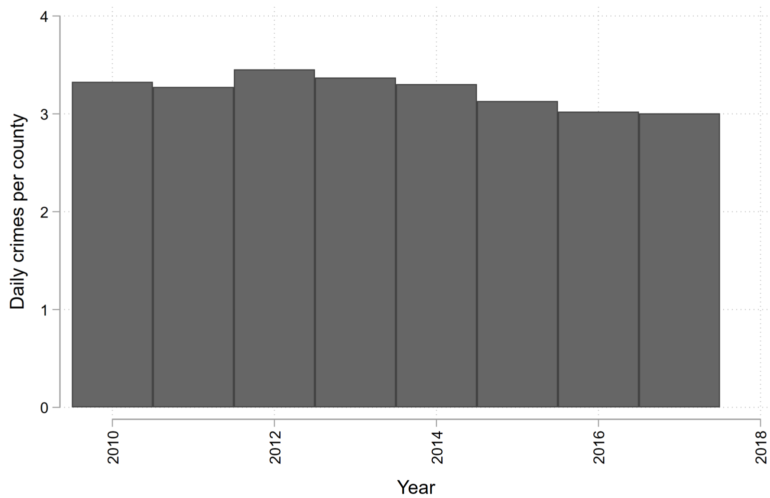
(b) Monthly hot days



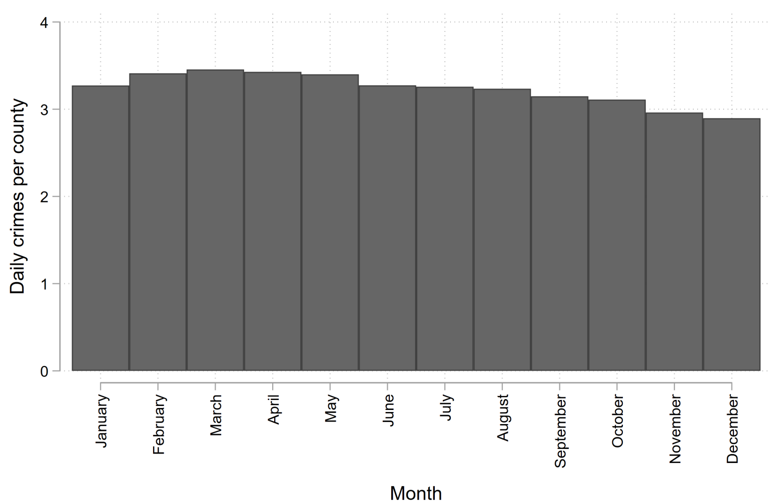
Notes: Panel A shows the trend in days > 90°F in three selected counties from each tercile of the distribution of the average number of hot days over the sample. Panel B shows the trend on average by month for the same counties to illustrate that there is significant variation across counties in our sample – both in the number of hot days from year to year and in the timing of those hot days throughout the year.

FIGURE A3: Total arrests

(A) ANNUAL ARRESTS

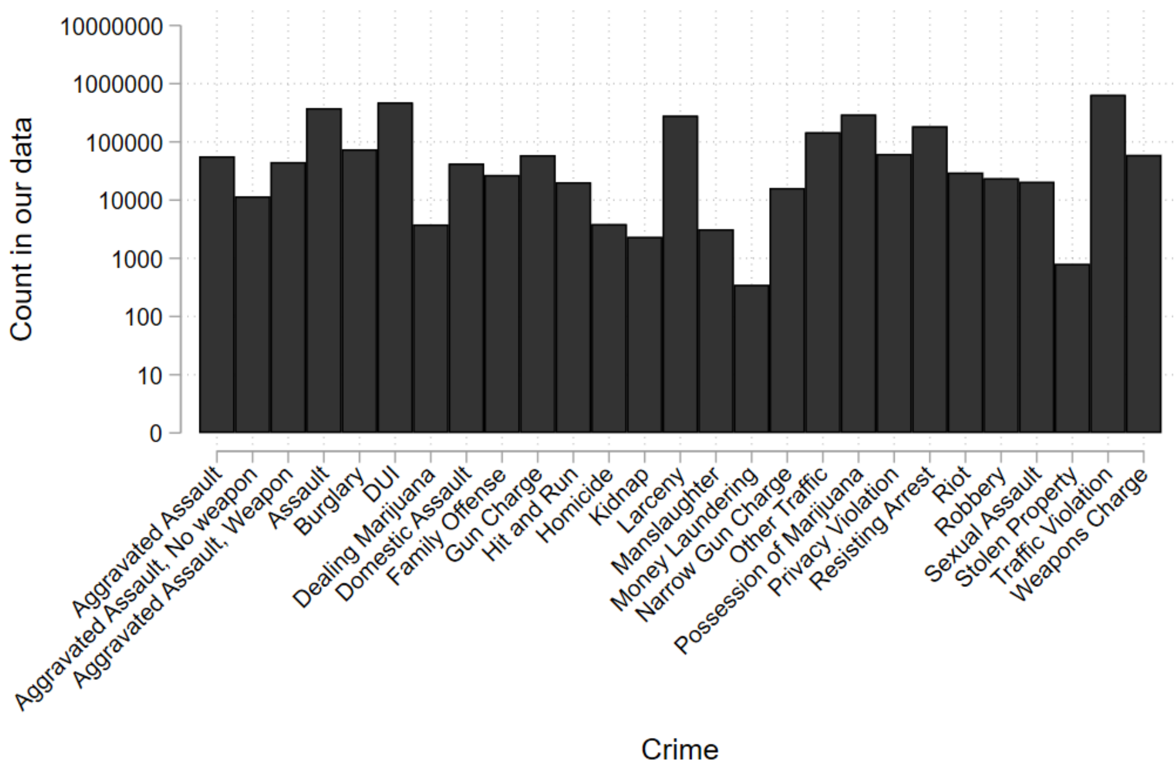


(B) MONTHLY ARRESTS



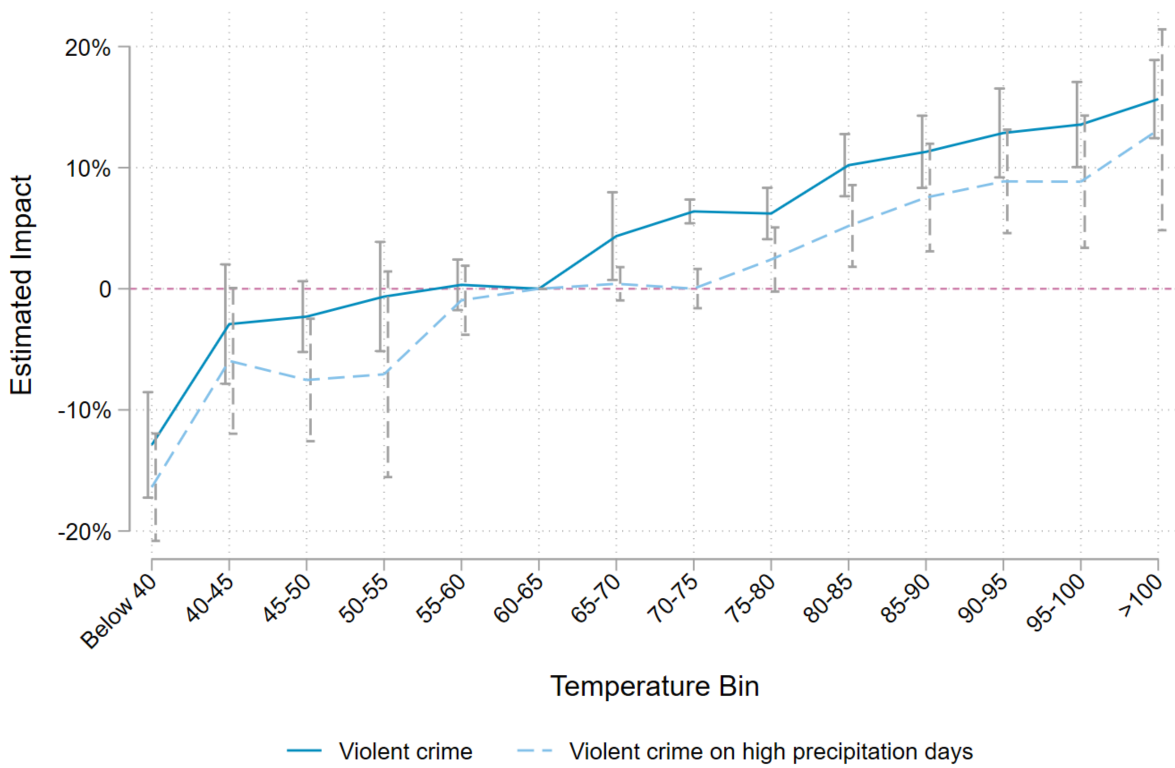
NOTES: Panel A shows the average daily arrests in each year, averaging across all Texas counties. Panel B shows the monthly average across all the counties and years in our sample.

FIGURE A4: Total arrests by crime



NOTES: Raw count of arrests across our full sample (2010-2017) by type of crime, prior to collapsing to block groups and counties. Note the log scale.

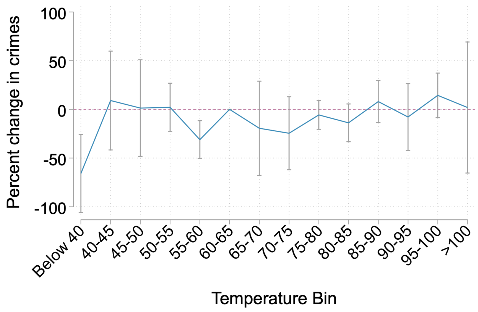
FIGURE A5: Heat's impact on violent crime on high precipitation days



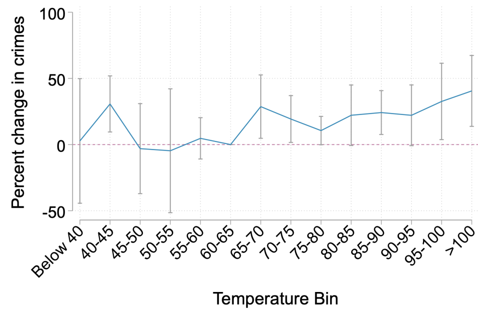
NOTES: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. In the solid line regression we control for precipitation in 3 bins. In the dashed line we interact all temperature bins with an indicator for whether the day was in our highest precipitation bin and report the total impact. In both we cluster errors at the county level. We weight by the total population in each county-year. Violent crimes are: manslaughter, homicide, kidnapping, sexual assault, domestic assault, aggravated assault, and assault.

Figure A6: Heat's impact on violent crimes

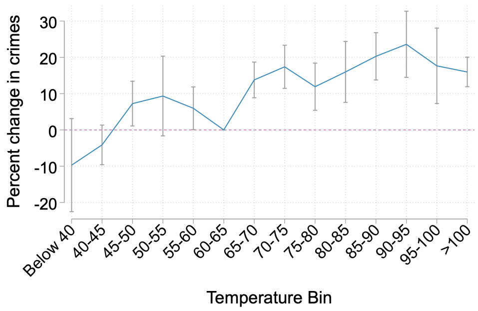
(a) Manslaughter



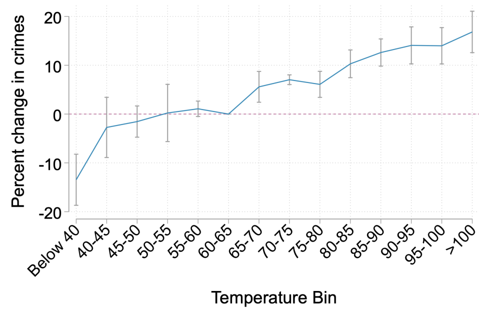
(b) Homicide



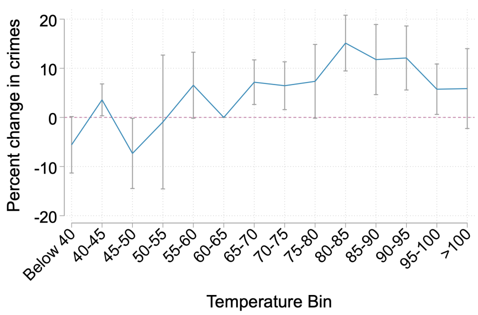
(c) Aggravated assault



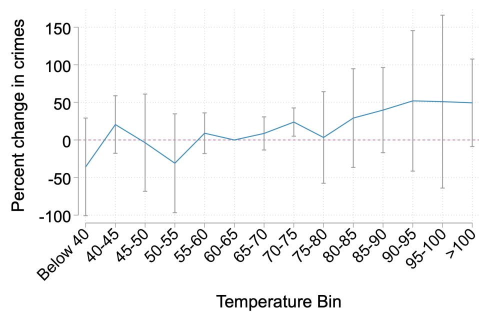
(d) Assault



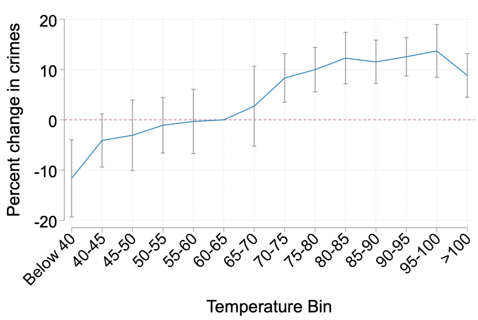
(e) Domestic assault



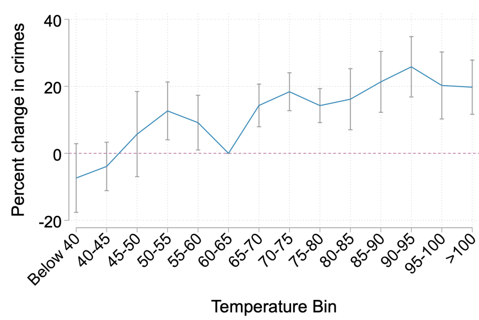
(f) Kidnapping



(g) Weapons crimes



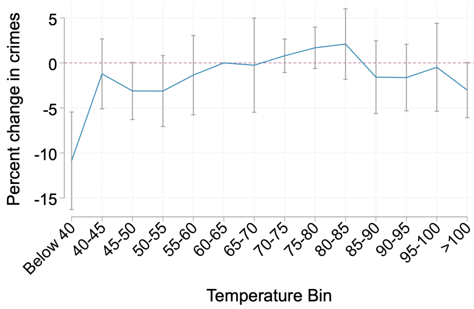
(h) Agg. assault, weapon



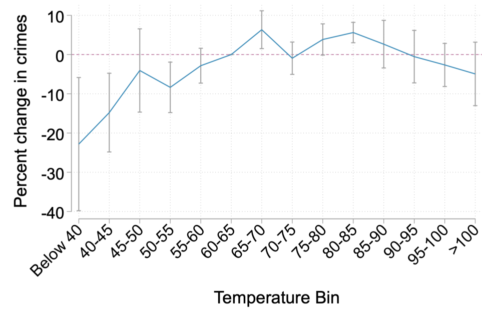
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control for precipitation in 3 bins and cluster errors at the county level. We weight by the total population in each county-year.

Figure A7: Heat's impact on non-violent crimes

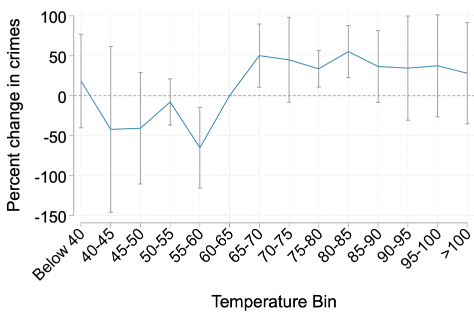
(a) Larceny



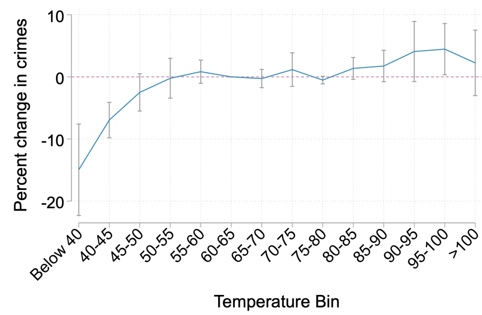
(b) Burglary



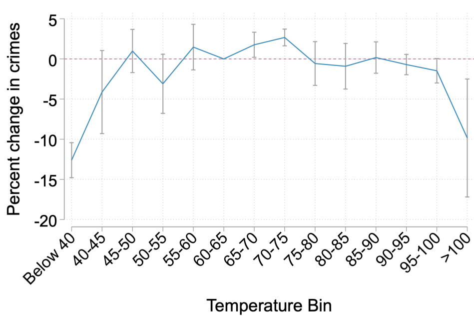
(c) Stolen property



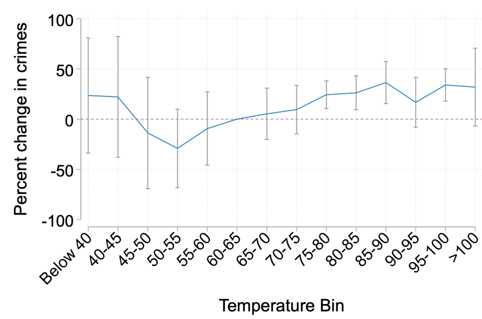
(d) Traffic



(e) Marijuana possession



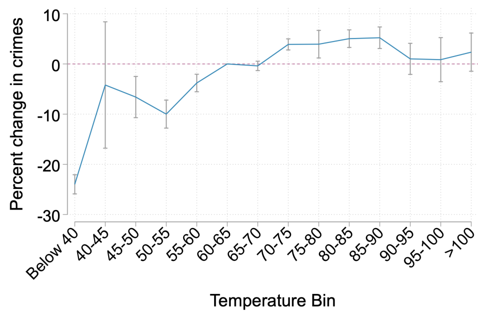
(f) Marijuana dealing



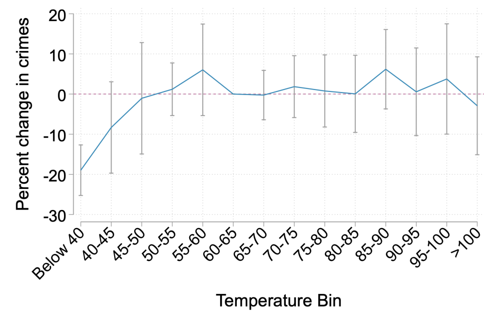
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65$°F day. Model includes county, year, month, and day of week fixed effects. We control for precipitation in 3 bins and cluster errors at the county level. We weight by the total population in each county-year.

Figure A8: Heat's impact on arrests for other crimes

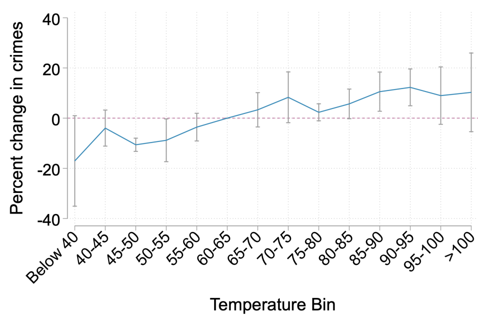
(a) Resisting police



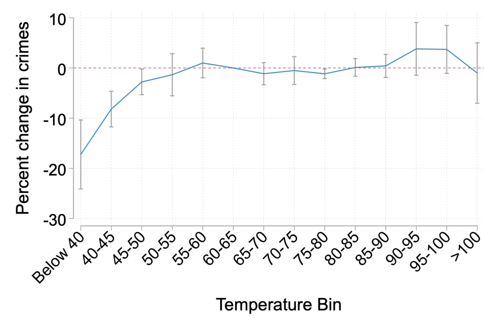
(b) Rioting



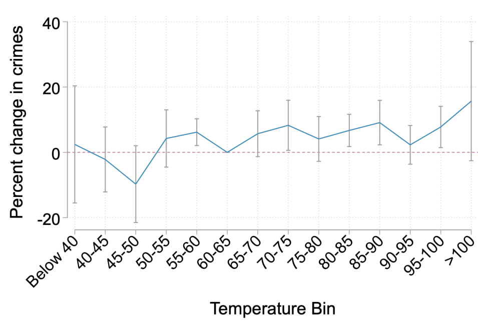
(c) Privacy violations



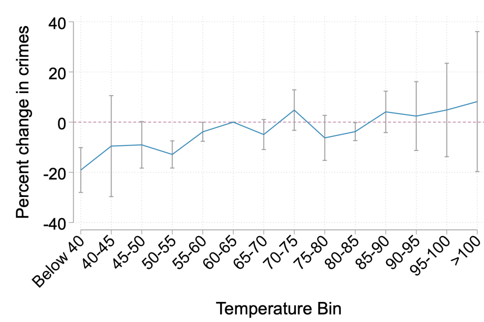
(d) DUI



(e) Hit & run

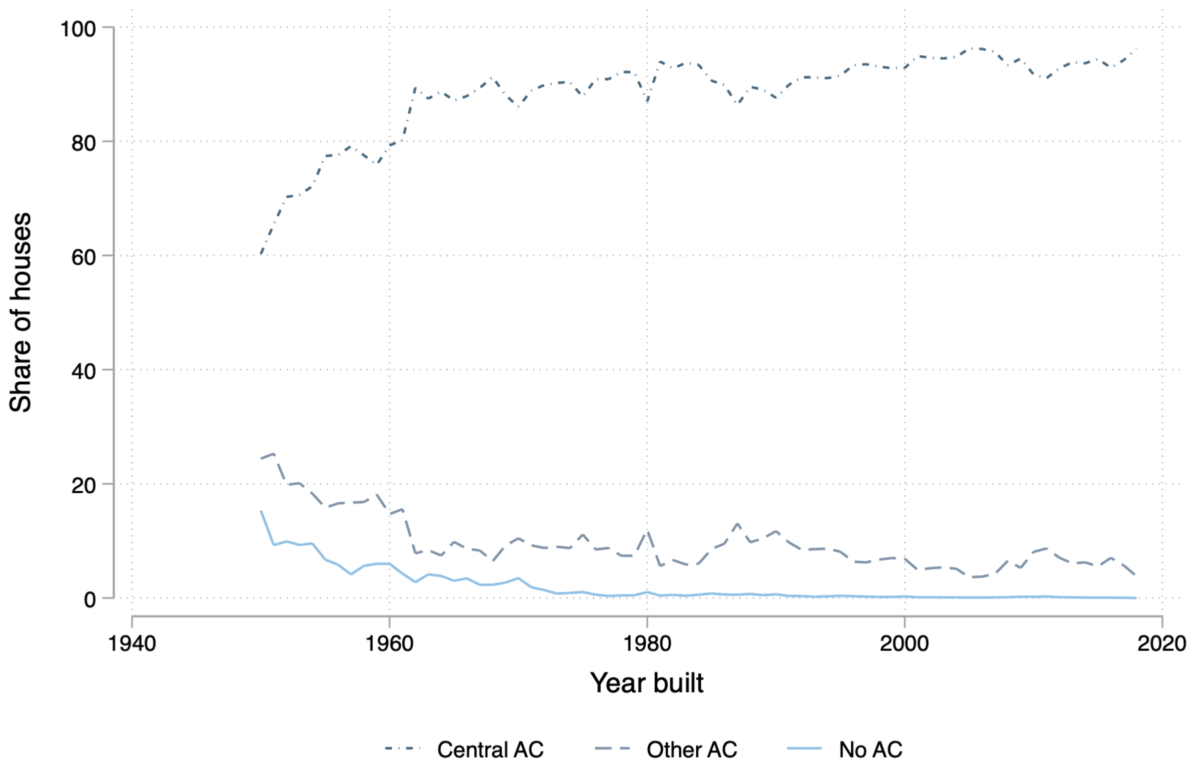


(f) Robbery



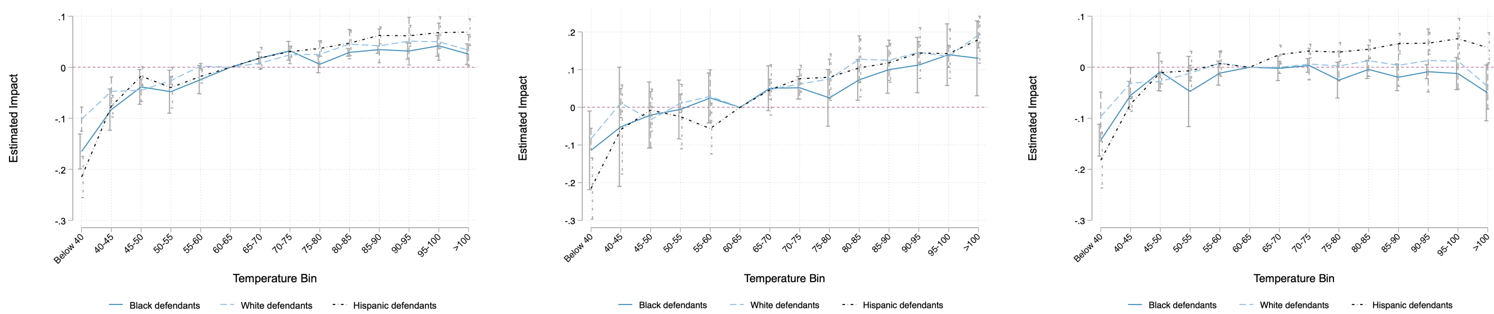
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control for precipitation in 3 bins and cluster errors at the county level. We weight by the total population in each county-year.

Figure A9: Air conditioning penetration



Notes: Categories are mutually exclusive - houses with other air conditioning do not have central air conditioning and vice versa. Data come from tax assessment records collected by CoreLogic. We bin houses built prior to 1950 into 1950. Only 10% of the houses in the CoreLogic Texas data are built before 1955.

Figure A10: Heat's impact on arrests by race and ethnicity

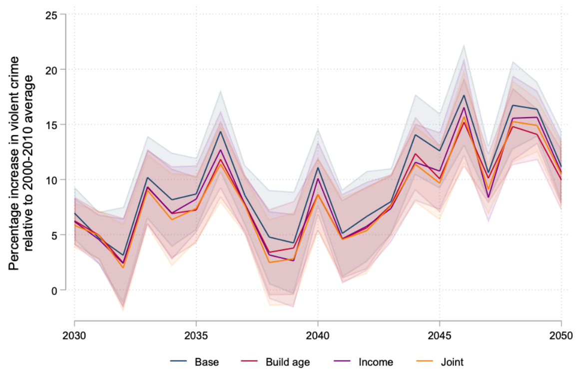


All crimes | Violent crimes | Non-violent crimes

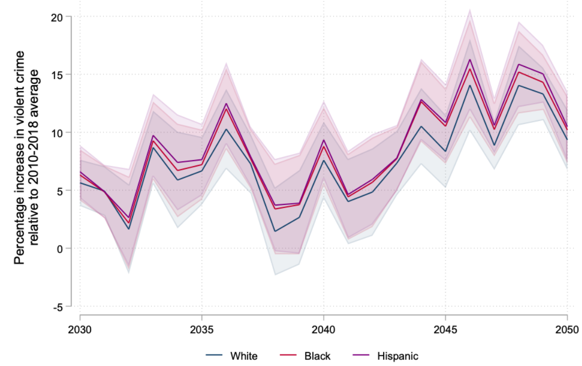
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65$°F day. Model includes county, year, month, and day of week fixed effects. We control for precipitation in 3 bins and cluster errors at the county level. We weight by the total population in each county-year. White refers to White, non-Hispanic defendants, while Hispanic are Hispanic defendants of any race.

FIGURE A11: Future impacts and uniform adaptation, RCP6.0

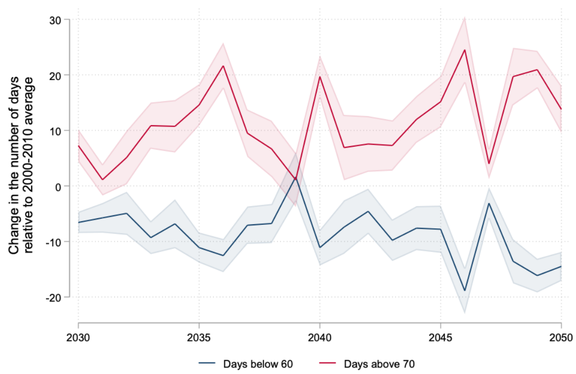
(A) Impacts by adaptation measure



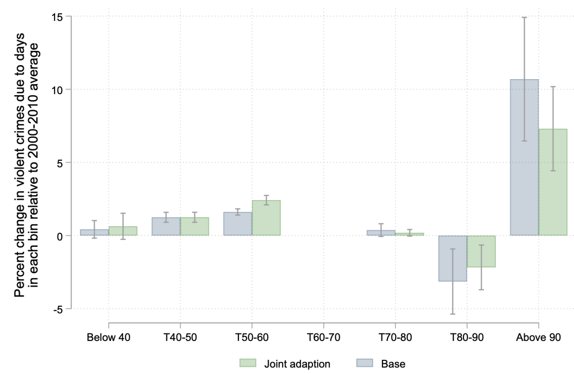
(B) Adaptation inclusive impacts by race



(C) Change in days above and below 60°F-70°F



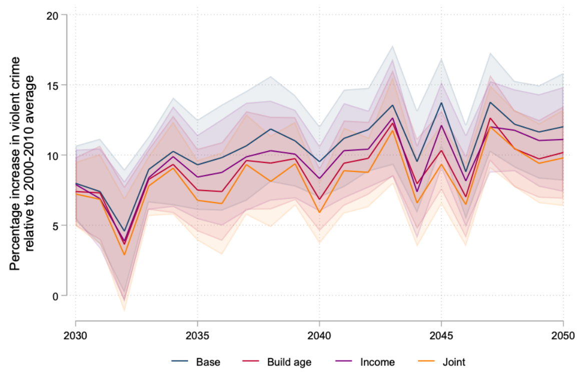
(D) Future impact by temperature bin 2050



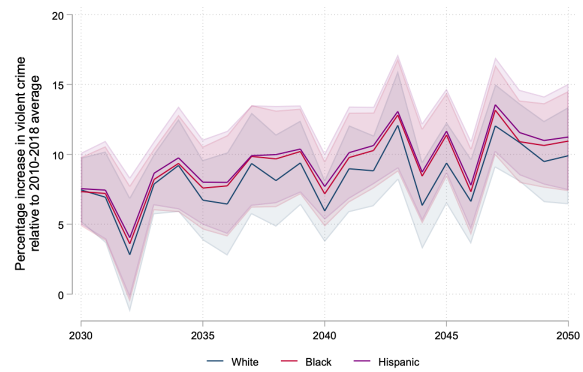
NOTES: In all panels we show results using projections under the RCP6.0 scenario. We grow incomes and housing stock age according to the U.S. average from 2002 to 2019 and the average over the Texas sample, respectively. In Panel **A**, we show the average percentage increase in violent crime across all of Texas due to the increase in average temperatures under four scenarios: using our pooled marginal estimates, using estimates that account for adaptation measured by the median building age, using estimates that account for adaptation measured by income, and using estimates that account for both building age and income. In Panel **B**, we show how the estimates accounting for both income and building age vary by race and ethnicity. Panel **C** shows how the number of days above 70°F, which generally increase crime, evolve compared with days below 60°F, which generally reduce crime. Panel **D** shows the product of our marginal effects by bin and the average total number of days in that bin in 2050 in the base scenario and the scenario accounting for building age and income. In all cases, we plot the average effect across all temperature models and show the 95% confidence intervals defined by the standard deviation of estimates across all temperature models.

Figure A12: Future impacts and adaptation, RCP2.6

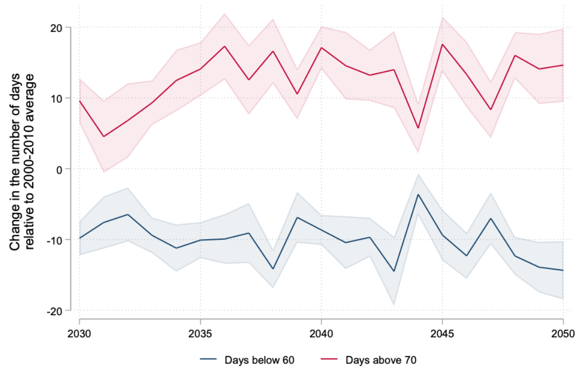
(a) Impacts by adaptation measure



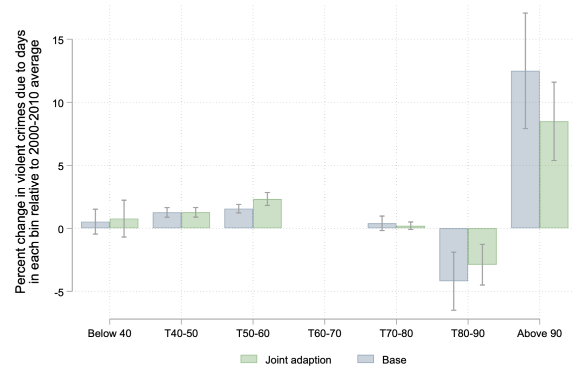
(b) Adaptation inclusive impacts by race



(c) Change in days above and below 60°F-70°F



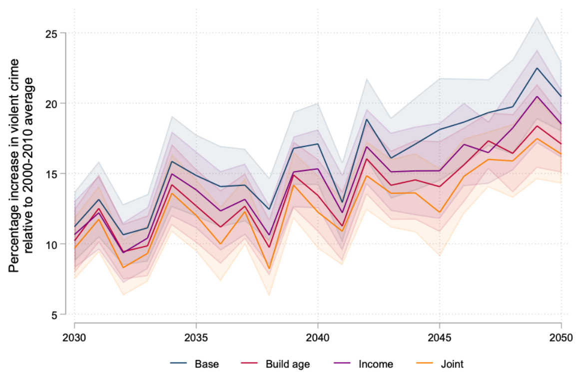
(d) Future impact by temperature bin 2050



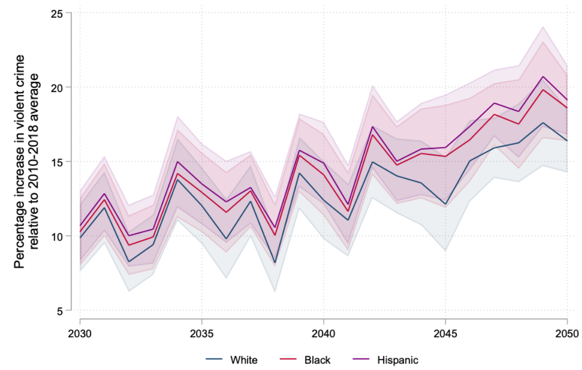
Notes: In all panels we show results using projections under the RCP2.6 scenario. In Panel **A**, we show the average percentage increase in violent crime across all of Texas due to the increase in average temperatures under four scenarios: using our pooled marginal estimates, using estimates that account for adaptation measured by the median building age, using estimates that account for adaptation measured by income, and using estimates that account for both building age and income. In Panel **B**, we show how the estimates accounting for both income and building age vary by race and ethnicity. Panel **C** shows how the number of days above 70°F, which generally increase crime, evolve compared with days below 60°F, which generally reduce crime. Panel **D** shows the product of our marginal effects by bin and the average total number of days in that bin in 2050 in the base scenario and the scenario accounting for building age and income. In all cases, we plot the average effect across all temperature models and show the 95% confidence intervals defined by the standard deviation of estimates across all temperature models.

Figure A13: Future impacts and adaptation, RCP8.5

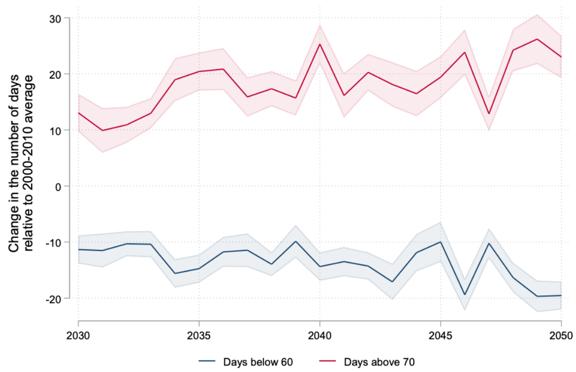
(a) Impacts by adaptation measure



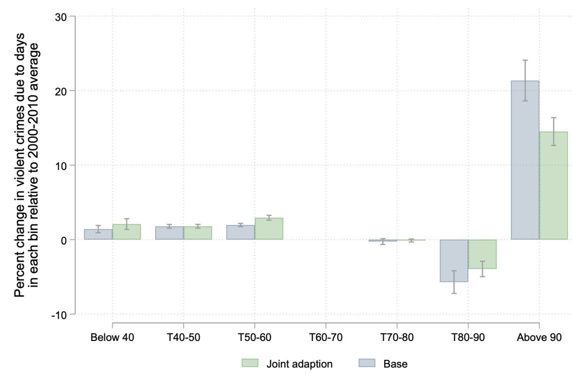
(b) Adaptation inclusive impacts by race



(c) Change in days above and below 60°F-70°F



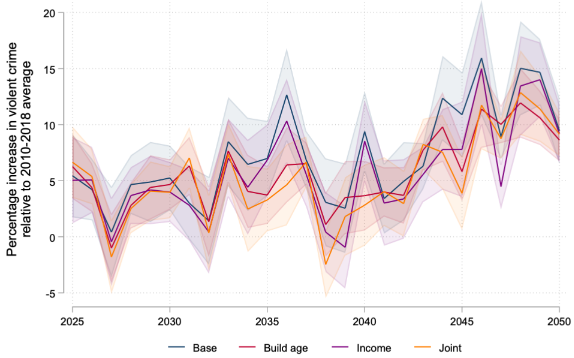
(d) Future impact by temperature bin 2050



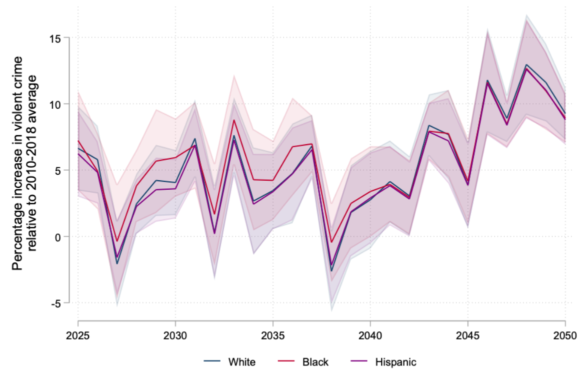
Notes: In all panels we show results using projections under the RCP8.5 scenario. In Panel **A**, we show the average percentage increase in violent crime across all of Texas due to the increase in average temperatures under four scenarios: using our pooled marginal estimates, using estimates that account for adaptation measured by the median building age, using estimates that account for adaptation measured by income, and using estimates that account for both building age and income. In Panel **B**, we show how the estimates accounting for both income and building age vary by race and ethnicity. Panel **C** shows how the number of days above 70°F, which generally increase crime, evolve compared with days below 60°F, which generally reduce crime. Panel **D** shows the product of our marginal effects by bin and the average total number of days in that bin in 2050 in the base scenario and the scenario accounting for building age and income. In all cases we plot the average effect across all temperature models and show the 95% confidence intervals defined by the standard deviation of estimates across all temperature models.

Figure A14: Future impacts and adaptation under aggressive adaptation

(a) Impacts by adaptation measure

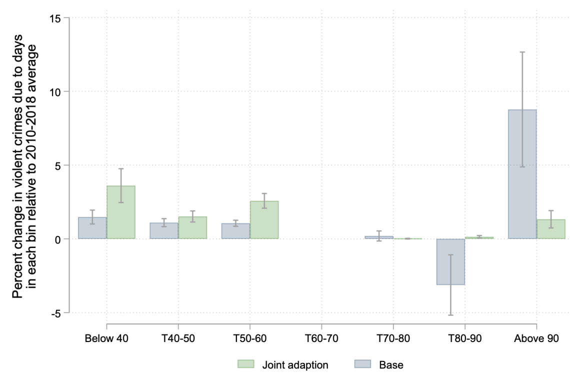


(b) Adaptation inclusive impacts by race



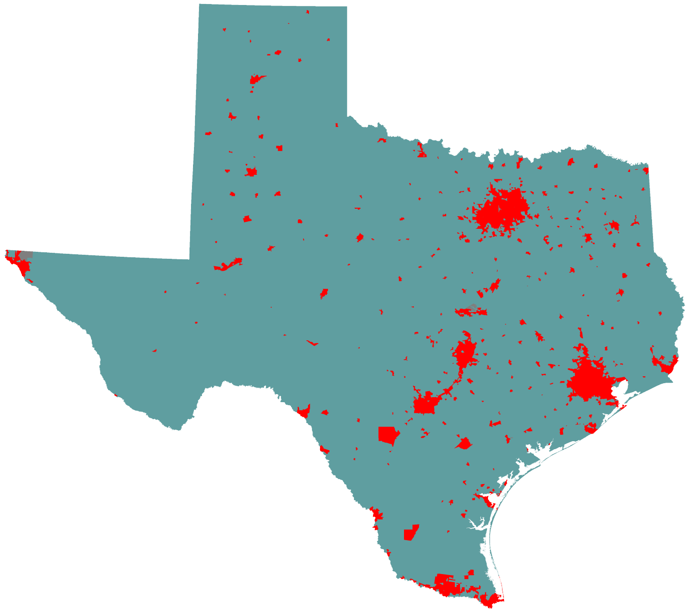
(c) Change in days above and below 60°F-70°F

(d) Future impact by temperature bin 2050

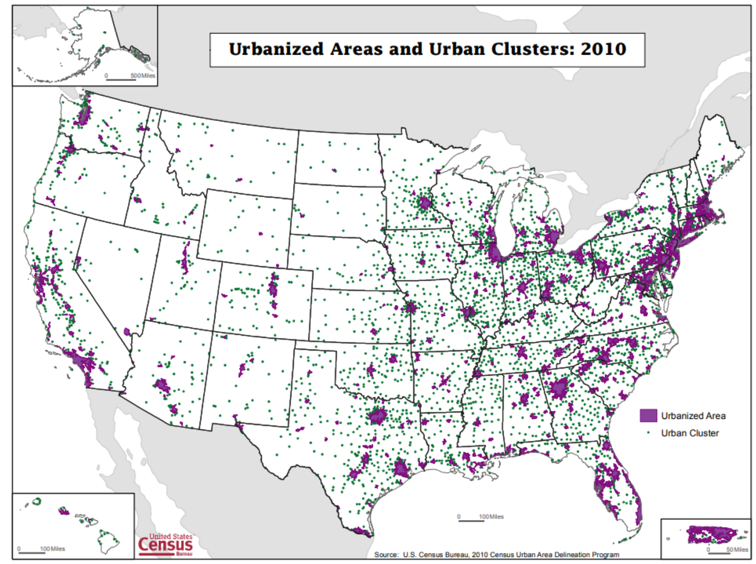


Notes: In all panels we show results using projections under the RCP6.0 scenario and our aggressive adaptation scenario. Our aggressive adaptation scenario assumes that income and building age grow at 10x the rate observed in our data. In Panel **A**, we show the average percentage increase in violent crime across all of Texas due to the increase in average temperatures under four scenarios: using our pooled marginal estimates, using estimates that account for adaptation measured by the median building age, using estimates that account for adaptation measured by income, and using estimates that account for both building age and income. In Panel **B**, we show how the estimates accounting for both income and building age vary by race and ethnicity. Panel **C** shows how the number of days above 70°F, which generally increase crime, evolve compared with days below 60°F, which generally reduce crime. Panel **D** shows the product of our marginal effects by bin and the average total number of days in that bin in 2050 in the base scenario and the scenario accounting for building age and income. The 60°F-70°F bin is omitted. In all cases we plot the average effect across all temperature models and show the 95% confidence intervals defined by the standard deviation of estimates across all temperature models.

Figure A15: Urban block groups

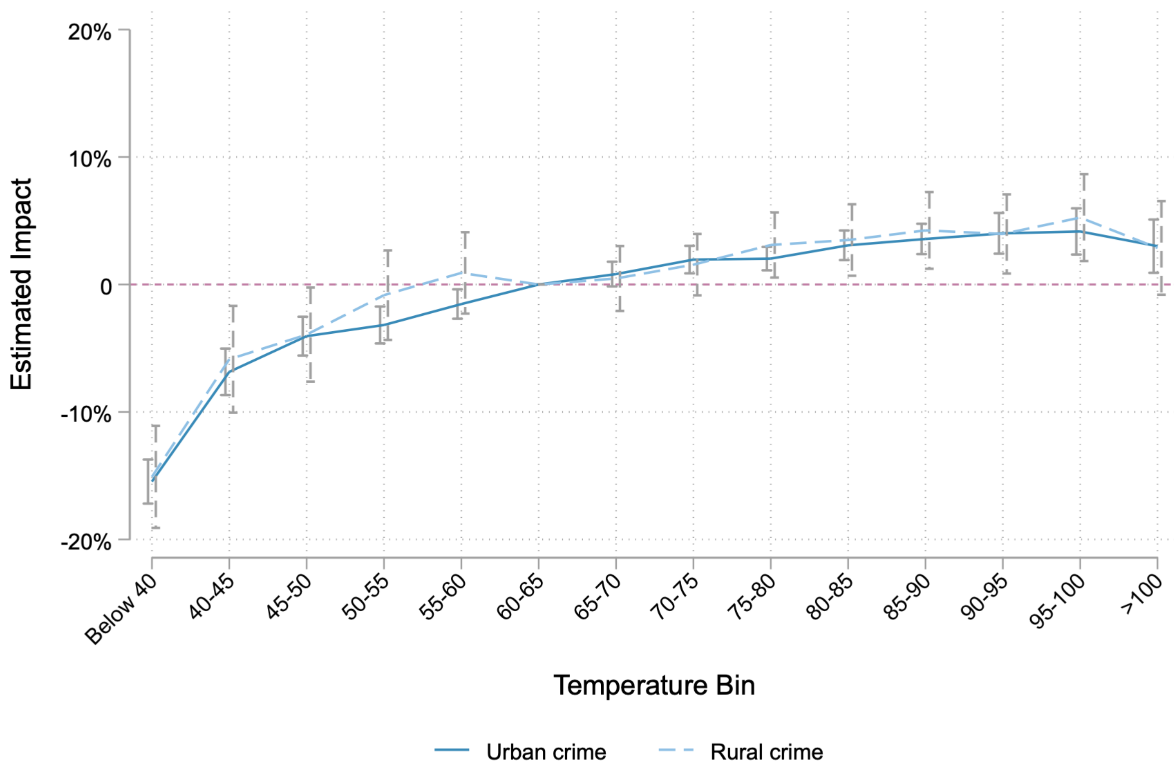


Notes: Red areas indicate block groups we consider urban. We categorize a block group as urban if 80% or more of the population is considered urban according to Census ACS data.



Notes: Map of areas the U.S. Census considered urban or an urban cluster in 2010.

FIGURE A16: Urban and rural crimes



NOTES: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in rural and urban block groups. We do not weight by population in this regression. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control for precipitation in 3 bins and cluster errors at the county level.