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Heat, Crime, and Punishment*

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In much of the world, a rapidly changing climate will result in more frequent extreme temperatures. Using administrative criminal records from Texas, we show how heat affects the behavior of key individuals involved in criminal events: defendants, police officers, prosecutors, and judges. We find that arrests increase by up to 15% on extremely hot days, driven by increases in violent crime rather than by changes in police behavior. We see no evidence that heat on the charging day impacts prosecutorial decisions, likely because prosecutors, like police officers, share emotional and cognitive burdens across team members. Working alone under time pressure, judges are less likely to dismiss cases, more likely to issue longer prison sentences, and more likely to levy higher fines when ruling on hot days. Our results suggest heat's negative impact on emotion and cognition leads to negative outcomes across situations and professions, even in Texas where air conditioning is nearly universal. We provide evidence that higher income, newer housing, more team work, and less accessible weapons may decrease the adverse effects of heat. Our adaptation-inclusive projections of the impact of future climate change suggest, however, that while adaptation will significantly mitigate future impacts, it will not eliminate them. Even with adaptation, climate change will likely also have substantial distributional consequences, with impacts on crime in more vulnerable communities up to 70% larger than in less vulnerable ones.
JEL Codes: Q5, H75, K42, D91.

* We thank Alex Bunin, Ishan Nath, Jisung Park, Marshall Burke, members of BurkeLab, participants in the 2021 LAGV conference, Natalia Emanuel, Rebecca Goldstein, Adrienne Harrold, Peter Hong, Wallis Nader, and Cassandra Richey at the Texas Department of Public Safety for their assistance and suggestions. We are also grateful to Robin Robinson for her excellent research assistance.

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Abstract

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"Reason is the slave of passion."

"The whole question here is: am I a monster, or a victim myself?"

— Fyodor Dostoyevsky, Crime and Punishment

1 Introduction

Heat increases criminal activity. This fact has been established by a wide literature across fields, including psychology, economics, and political science. Individual criminal activity increases on hotter days (Ranson, 2014) and intra-group conflict increases with increases in heat (Burke et al., 2015). What drives the increase in interpersonal conflict, and individuals' commission of crimes in particular, remains unclear.

Various explanations for the effect of heat on 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 mediating aggressive behavior (Anderson, 1989; Anderson et al., 2000; Baron and Bell, 1976). More recent economics work has also examined how the impact of heat on crime varies across neighborhood characteristics - heat appears to have larger impacts in older and poorer neighborhoods - to suggest that heat's differential effects may be a manifestation of differential investment in early childhood coupled with underlying psychological mechanisms (Heilmann et al., 2021).

A clear implication of a psychological explanation for the increase in crime on hotter days is that heat may not only impact potential criminal defendants but also the police charged with arresting them, the prosecutors responsible for prosecuting them, and the judges who ultimately preside over their trials. Despite the robust literature on heat and crime, there has been much less attention given to how heat impacts the whole range of actors in the judicial system. Two recent papers work to address this gap: Obradovich et al. (2018) suggests that heat can reduce police effort and, studying immigration judges, Heyes and Saberian (2019) measures a decline in asylum grants when judges issue decisions on hot days.

In this paper, we re-examine the question of heat's impact 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, with comprehensive data on the subsequent prosecution and trials of these arrests, we examine how heat impacts the commission of crimes and the defendants' subsequent judicial outcomes. Our data are unique in providing detail at the individual defendant level across a large geographic region and in including outcomes in the judicial process. We couple these data with data on all crimes reported in the jurisdiction of the Houston Police Department, the 5^{th} largest in the United States, to examine how heat affects arrests relative to reported crimes.

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. Crucially, these data provide dates associated with major decisions: the date of arrest, the date on which the prosecutor files charge(s), and the date on which the judge makes a ruling. 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, as well as on decisions made by prosecutors and judges.

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 either focusing on a wide geographic region but with little detail on individual defendants or temporal resolution (e.g., Ranson (2014)), or to using detailed information for a smaller geography, generally a single city (e.g., Heilmann et al. (2021); Harries et al. (1984)).[1] 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 in 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 heterogeneity analysis than existing work. Much of this work has relied on reported crime data (e.g., Ranson (2014); Heilmann

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

et al. (2021)) and so uses information about the location of the crime (or report), but not the residence of the defendant.[2] 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 mediate the relationship between heat and crime.

The richness of our data on the built environment in which defendants reside also allows us to conduct an extensive examination of how adaptation could mitigate the effects of future climate change. We measure how the impact of heat varies across different levels of a range of neighborhood adaptation markers, using the variation in impacts to predict the effectiveness of future adaptation. Combined with the output of more than 40 global circulation models (GCM), we use these predictions to examine how adaptation mitigates the impact of predicted changes in exposure to high temperatures in Texas.

Finally, we examine how heat impacts outcomes in the judicial process by tracing the entire arc of a case. We study how heat on the day of the arrest impacts outcomes for an individual defendant and, separately, how heat impacts the decisions that prosecutors and judges make. Our data, covering criminal prosecutions, provide a much richer set of outcomes with which to examine judge behavior than existing work that has focused on parole and immigration courts (Heyes and Saberian, 2019).

We find 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 suggests that we are in fact measuring increases in crime, and not the effect of heat on police behavior. We test this hypothesis directly using crime reported to the Houston Police Department, finding that reported crimes increase substantially more than arrests on hot days. 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

[2] Levy et al. (2020) demonstrate 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.

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, and that 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 to protect themselves from heat that arise from differences in housing stock, rather than from differences in childhood investments (Heilmann et al., 2021).

The effect of heat reverberates throughout the judicial process, even though climate control is ubiquitous in Texas. While data on climate control in prosecutor offices and courtrooms are not readily available, it is likely that penetration rates in these buildings are similar to those in residential buildings, where CoreLogic data suggest coverage is 97%. Individuals arrested on hot days are more likely to have their case dismissed, even after accounting for mechanical changes in dismissal rates due to changes in the types of arrests (i.e., more violent arrests) that occur on hot days. Our conversations with attorneys suggest this is due to police officers being more likely to make arrests that prosecutors choose not to prosecute or that judges decide to dismiss.

Taking advantage of the fact that prosecutors present their charges and judges hand down rulings on average five months after the arrest, we study how heat on the day of the charge filing and the court ruling affects prosecutors and judges. Prosecutors appear to be unaffected by heat on the day of the charge filing, likely because the decision-making in the process happens over many days and in a team. Judges, on the other hand, are adversely affected by heat. Judges are less likely to dismiss cases and, conditional on conviction, more likely to hand down harsher sentences on hot days. The fact that judges are overworked, have a limited amount of time to determine sentence severity, and have to do so by themselves likely makes them more susceptible to the effects of heat. As in Heyes and Saberian (2019), we record these effects even though judges work in climate-controlled environments.

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, crimes increase in similar ways in neighborhoods with a majority population in each of these three groups, and outcomes in the judicial system are broadly consistent.

Lastly, 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. 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 violent crime arrests still increase by 9% per year by 2050. The impacts of this future climate change are not spread evenly across the population, primarily because adaptation will not occur evenly. Lower income areas see increases in crime that are roughly 70% larger than high income areas and minority neighborhoods see increases that are $\approx$20% higher than White neighborhoods. We also take advantage of our data on convictions to predict how the total probability of arrest and conviction will change in a warmer world. We find that, absent adaptation, Texans will see a 12% increase in the probability of arrest and conviction relative to present day levels.

Overall, our results lend strong support to a psychological mechanism for the impact of heat on crime. While other mechanisms may be able to explain individual features of our results, the psychological mechanism provides a consistent theory that unifies the full set of our findings. Heat reduces self-control, negatively impacts mood, increases aggression, and places heightened stress on cognitive faculties. As a consequence, violent crime increases, individuals are more likely to reach for weapons when they are available, and judges working on tight schedules - as opposed to prosecutors who operate in a team on looser deadlines - make harsher and more punitive judgements. A psychological explanation does not preclude other mechanisms from operating in certain circumstances, including ours, but no other single theory offers a consistent explanation for the full set of our results.

Our results also provide additional evidence for the regressive impacts of climate change. Future increases in heat appear to increase criminal arrests and to increase them substantially more in more vulnerable communities. These future increases occur despite significant mitigation of the impacts of climate change by adaptation. In fact, it may be the case that disparities in future adaptation increase the regressivity of climate change impacts. Our results highlight that it is not only climate mitigation policies (Peng et al., 2021), but also differences in climate adaptation, that 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. Sections 5 - 7 report the effects of heat on arrests and prosecutorial and judicial decisions. Section 8 presents estimates for how the probability of arrest and conviction will change due to climate change. Section 9 concludes.

2 Conceptual Framework

There is a robust literature both inside and outside of economics on the positive 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 et al., 2021; 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 et al. (2021) use data on criminal and police activity in L.A. to test this hypothesis and finds little support for it. Alternatively, heat may have negative impacts on legal sources of income (e.g., by reducing crop yields) and so increase the benefits of committing crime.[3] Blakeslee et al. (2018) finds evidence that property crimes in India do increase after heat-driven crop failures and suggests that this is evidence for heat operating through an economic channel for certain types of crimes. Similarly, Garg et al. (2020) find that an income support program in Mexico substantially reduces the sensitivity of homicides to high temperatures. They cannot clearly identify whether this is because the additional income allows for protective investments (e.g., the use of air conditioning) or because it mediates the impacts of heat driven economic shocks.

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. 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 et al., 2021; Blakeslee et al., 2018; Mukherjee and Sanders, 2021). Heilmann et al. (2021) 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).

Heat's negative impacts on psychological control as the mechanism for heat's impact on crime rates is consistent with a broad recent literature that finds heat has negative impacts on cognitive

[3] In light of our subsequent discussion of psychological motivations for crime, it is worth noting that crop failures also have psychological consequences (Carleton, 2017) that might lead to increases in crime for non-economic reasons.

and non-cognitive skills in a range of settings (Graff Zivin et al., 2017). Heat has been shown to reduce student performance in both the short (Park et al., 2020b; Park, 2020) and long-term (Park et al., 2020a). Laboratory studies have shown that performance of both cognitive and non-cognitive tasks declines as temperature increases (Ramsey, 1995; Hocking et al., 2001; Seppanen et al., 2006). Non-police government officials appear to be less zealous in the execution of their duties on hotter days (Obradovich et al., 2018) and consumers rely more on heuristics for decision-making when subjected to heat stress (Cheema and Patrick, 2012).

The expansive impact of heat on psychological control that has been documented in existing work lends support to the claim that heat's impact on crime - at least in wealthier, non-agricultural communities - operates via a psychological channel. But it also raises an important difficulty with much of the existing work. Heat impacts not only those who may be committing crimes but also those who are responsible for pursuing these crimes, deciding what to prosecute, and adjudicating the ultimate trial. Existing work has focused almost exclusively on the impact of heat on the commission of crimes, as opposed to policing or trial outcomes.[4]

The existing focus on heat's impact on criminal activity leaves aside the important question of what impact heat has on the entirety of the criminal justice system. Heat's cognitive and non-cognitive impacts are not limited to potential criminal defendants but also impact police, prosecutors, and judges. These impacts have important implications for both how crimes are pursued and the overall outcomes for defendants in the criminal justice system.

To clarify these points, consider the following analytic framework. We express arrests (A) as a function of criminal (C) and police (P) activity, both of which are determined, in part, by temperature:

$$Arrests = A(C, P) \tag{1}$$

How do arrests evolve with changes in temperature (T), which we define as deviations from the optimum temperature? It will depend on the combined impact of temperature on criminal and police activity.

[4]There are some notable exceptions. As noted, Obradovich et al. (2018) finds police are less likely to stop motorists on hot days and Heyes and Saberian (2019) finds that U.S. immigration judges issue fewer asylum requests. In a study primarily on air pollution, Kahn and Li (2020) also find that heat has no impact on judges' processing time in China.

$$\frac{dA}{dT} = \underbrace{\frac{\partial C}{\partial T}}_{(1)} + \underbrace{\frac{\partial C}{\partial P}\frac{dP}{dT}}_{(2)} + \underbrace{\frac{\partial P}{\partial T}}_{(3)} + \underbrace{\frac{\partial P}{\partial C}\frac{dC}{dT}}_{(4)} \tag{2}$$

The four terms on the right hand side capture different aspects of the relationship between heat and arrests. Terms one and two capture the direct impact of heat on criminal activity and the "rational criminal" response to temperature: term 1 captures the direct impact of heat on criminal defendants. Term 2 reflects how crime changes in response to changes in police activity driven by temperature changes. The total effect of these two terms is the object most existing work on heat and crime, using data on reported crimes, has estimated.[5] Term three captures the direct impact of heat on police activity (the effect estimated by Obradovich et al. (2018)). Term four captures any changes in police effort in response to changes in crime due to heat: if, for example, police increase patrols on hot days because they know crime increases on these days.

Heat may impact police activity for many of the same reasons that it impacts criminal activity. Obradovich et al. (2018) finds police are less active in the heat, arguably because exerting effort on hot days is more costly. This is consistent with a broad literature that finds reductions in labor supply and productivity on hot days in a variety of settings (Graff Zivin and Neidell, 2014; Somanathan et al., 2015). If these negative impacts dominate any change in behavior due to anticipated changes in crime this would manifest as an overall negative sign on term four.[6]

Heat may also, however, make the police more likely to arrest individuals relative to cooler days (i.e. term 3 may be positive). There are at least two reasons for this. If heat increases aggression and violence in the commission of crimes, police may pre-emptively arrest individuals to defuse a situation that heat-driven aggression has exacerbated in a way that would not have occurred on a cooler day. Police officers may also arrest more frequently on hotter days because the officers themselves become more aggressive. Existing work suggests that police are negatively impacted by hot temperatures in ways that make them more aggressive, more tense, and produce more negative views of defendants (Vrij et al., 1994). Heat also appears to increase out-group bias (Blakeslee et al., 2018) and may strengthen the pre-existing biases of police officers. All of these effects -

[5]The best estimates of term two suggest that it is zero or close to zero and the majority of the existing effect operates through term one (Heilmann et al., 2021).

[6]Heilmann et al. (2021) use data on instances when LAPD officers leave their cars and find that this actually appears to increase on hotter days, suggesting that term four may be slightly positive. They do confirm a decline in traffic stops, consistent with (Obradovich et al., 2018).

pre-emptive arrests, increases in police aggression, or increased bias - would suggest a positive sign on term three. The strength of that impact is likely to vary with types of crime, however. Crimes that involve violence, assault for example, may be more likely to see increases driven by pre-emptive arrests or police aggression, while crimes where police have more discretion are likelier to see increases due to possible changes in bias. Crimes with neither of these features, larceny for example, are potentially less likely to see changes driven by police activity.

Capturing the full effect of heat on arrests is important from a welfare perspective. Existing work demonstrates that heat imposes substantial welfare costs by increasing criminal activity. But arrests and incarceration also impose welfare costs, particularly on those who are arrested (Mueller-Smith, 2015; Pettus-Davis et al., 2016; Provencher and Conway, 2019). Understanding the extent to which arrests increase on hot days because of heat's impact on police, as opposed to increases in crime, thus has important implications for how the welfare costs of heat driven changes in crime are distributed. Conversely, if arrests on hot days do not keep pace with increases in crime because of declines in police effort that suggests there is a substantial welfare cost that is being shifted onto the victims of crimes that could be alleviated by increased police effort.

The overall impact of heat on welfare in the criminal justice system also depends on how heat impacts outcomes for defendants after crimes and arrests have occurred. It is well known that judges can be influenced by apparently extraneous factors such as the losses of local college sports teams (Eren and Mocan, 2018). Heat itself has been shown to reduce judge's granting of asylum in U.S. immigration courts, even in setting with pervasive air conditioning (Heyes and Saberian, 2019). Prosecutors are also not free from bias in their decisions (Didwania, 2018), although no evidence to date has shown that they are influenced by heat.

Judges and prosecutors may be influenced by heat for the same reason as criminals and police officers or workers in other settings. We have already discussed the impacts of heat on emotional affect and mood, factors that clearly impact prosecutorial and judicial decisions, but there is also abundant evidence that heat negatively impacts higher order cognitive function (e.g., (Graff Zivin et al., 2017)). Thus, heat may influence judge and prosecutor decisions through its impacts on both cognitive and non-cognitive functions.

3 Data

3.1 Texas Department of Public Safety (TDPS) Data

We start with confidential data from the TDPS that include detailed information about every arrest made in Texas from 2010 to 2017. These data are collected and organized by the TDPS and come from direct reports from individual counties to the state. Texas state law requires that counties report these data to the TDPS annually in order to receive funding from a variety of state grant programs. Further, counties must maintain at least a 90% completeness rate of these reports over a rolling five year period in order to be eligible for funding. We received our data in 2019, meaning that data through 2017 have been deemed to contain at least 90% of all arrests made in Texas (Department of Public Safety, 2019).

The TDPS 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 provides 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 (e.g., misdemeanor A), the arrest charge (e.g., 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.

The prosecution data can be linked to the individual and arrest data using the unique individual and incident IDs. They include the prosecuting agency, date the prosecutor took action on the case, the action taken, the level of the offense that was prosecuted, and the charge prosecuted. The court data include the court that tried the case, the date of the trial, the final pleading of the defendant, the level of the offense and charge that the court ruled on, the sentence handed down by the court, the length of any court ordered probation or confinement, the amount of any court costs 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 the date of arrest and date of offense these dates are the same for 84% of these arrests. We run robustness checks using the date of offense and find broadly similar results.

defendant was ordered to pay, and the amount of any fines the defendant was ordered to pay. The data also include whether the case was appealed and the outcome of the appeal. We link arrest and prosecution charges to the court data using the unique individual and incident IDs.

We drop all arrests and charges for which we do not have court outcome data (i.e., the 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 (e.g., violent crimes, assaults, etc).

3.2 Crime Reports from the Houston Police Department

We supplement our TDPS data on arrests with daily data from the Houston police department, the largest city police department in Texas and the fifth largest by officer count in the United States (Reaves and Hickman, 2008), on reported crimes. These data report the date, hour, location, and type of crime committed from 2010 through 2018. We categorize crimes into violent and non-violent using the same categorization rules used with the TDPS data and we geocode the provided locations to match the incidents to the U.S. Census tracts associated with each address. Addresses in the Houston PD data correspond to the location from which each report was filed – not, as in the TDPS data, to the address at which the defendant lived at the time. To account for this, and to account for the fact that defendants may commit crimes in Houston even if they do not live in Houston, we create a sample of arrests from the TDPS data that matches the incident data. We do so by pulling all arrests between 2010 and 2017 where the address of the defendant was in one of the five counties of the greater Houston area. We match these addresses to census tracts as well, in order to facilitate comparisons between reported incidents and arrests.

[8] These are indicated as cases where the result is "pending" or "no determination."

3.3 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.

3.4 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 groups 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 as defined as urban by the ACS.

3.5 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 1 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 2. 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 3 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. Slightly fewer than three quarters of these are misdemeanors, with the rest being felonies. White, non-Hispanic individuals commit the largest number of crimes in our data, reflecting their plurality in the overall population. Figure 4 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.

Figure 5 shows the raw counts of selected crimes within our data. We focus here on crimes we include in the violent or non-violent categories, so this is not an exhaustive list of all the crimes in our data. There is substantial variation in the number of different crimes in our data. For example, we see roughly 20× as many assault charges as manslaughter charges. Within the subset of crimes we classify into violent and non-violent, the most frequent are assault, DUI, larceny, and non-DUI traffic violations.

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 (e.g., Ranson (2014)). We assume the standard exponential form for the conditional mean ($\mu(\mathbf{X}_{idmy})$) of crimes (C_{idmy}) given our covariates ($\mathbf{X}_{idmy}$) and take the logs of both sides to get our estimating equation:

$$log\Big(\mu(\mathbf{X}_{idmy})\Big) = \beta_k \sum T_{idmyk} + \rho_l \sum R_{idmyl} + \delta_y + \psi_i + \eta_d + \Omega_m \tag{3}$$

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 1^{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 (e.g., there may be more crimes on Fridays) and the year (e.g., 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 (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.[9] We cluster

[9] The precise interpretation of β is the difference in the logs of the expected count of crimes. For small changes,

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).

Further, the fixed effects Poisson, estimated using maximum likelihood, produces unbiased estimates of the coefficients even if the crimes data does not exactly match the Poisson distributional assumptions (Wooldridge, 1997, 1999; Lin and Wooldridge, 2019). The same cannot be said for other common approaches to dealing with data with many zeros, like the negative binomial or zero-inflation model (Blackburn, 2015). Another advantage of the fixed effects Poisson is that it avoids the incidental parameters problem (Charbonneau, 2012; Cameron and Trivedi, 2001), which allows us to estimate a model with a large number of geographic and temporal fixed effects.

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.

4.2 Analysis of Outcomes in the Justice System

In addition to analyzing the impact of heat on arrests, we examine how being arrested on a hot days impacts outcomes for defendants in the justice system and, separately, how heat on the day of decisions impacts prosecutor and judge decision making. In our analysis of these outcomes we take a similar empirical approach as in the arrests analysis, but we rely on a linear fixed effects model

this is approximately equal to the percent change in the count of crimes.

rather than a Poisson model. When analyzing arrests, it is important that we include days with zero arrests so as not to condition our analysis on being arrested. That results in many county-days with zero arrests, which motivates our choice of the Poisson specification. In our analysis of judicial outcomes, however, there is no need to include days on which there was no arrest or no prosecutorial or judicial action. There can be no judicial outcome if there is no action. Rather, we would like to know how heat changes the probability of an outcome conditional on action occurring. As a result, our data on outcomes in the judicial system, unlike our results on arrests, do not have many days with zeros that need to be accommodated by our estimating equation. Therefore a linear fixed effects model is appropriate here, rather than the Poisson approach.

For these analyses we thus focus on individual cases and estimate regressions of the form

$$Y_{pidmy} = \beta_k \sum T_{idmyk} + \rho_l \sum R_{idmyl} + \delta_y + \psi_i + \eta_d + \Omega_m \tag{4}$$

where the common elements with equation 3 are as before and Y_{pidmy} represents our outcome of interest for defendant p (e.g., an indicator for whether an arrest resulted in a conviction or the length of defendant p's sentence). Again, our identification rests on plausibly exogenous variation in the temperature on the day of the arrest for defendant p net of any year, month, or day of the week specific variation in temperature or outcomes. In our analysis of prosecutor and judicial decision making, T_{idmyk} represents the temperature on the day that the prosecutor or judge made a decision in the case of defendant p. Our outcome of interest is again β_k, which in this specification estimates the increase in the probability that a case arrested on a hot day (or decided on a hot day, depending on the analysis) experiences a given judicial outcome Y_{pidmy}.

5 Results I: 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 impact of heat varies by neighborhood characteristics, in particular the age of the housing stock and various measures of neighborhood wealth and income. Next we look at whether individuals arrested on hot days have differential judicial outcomes from those arrested on cooler days. Finally, we examine how the introduction of an open carry law in Texas in 2016 interacted with heat's impact on crimes related to weapon use.

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 6 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. Like much of the existing work on the impacts of temperature (e.g., (Park et al., 2020a), (Heilmann et al., 2021)) our results indicate that heat's impact increases linearly in temperature. These results are robust to alternative fixed effects specifications as well as to controls for humidity like dew point and vapor pressure deficit (see columns 5 and 6 of Table A1). They are also robust to using data on the date of offense rather than the date of arrest (Table A2) and to including up to 5 lags of daily temperature (Table A3). Our results provide strong evidence that heat increases arrests and that the impacts are highest at the highest temperatures. This is in line with existing work on the impact of high temperatures on crime using reporting data, which find between a 2 and 9% effect (Ranson, 2014; Heilmann et al., 2021; Schinasi and Hamra, 2017).

5.2 Heat's Impacts are Largest for Violent Crime Arrests

We turn next to the impact of heat on individual crimes, specifically on violent and non-violent crimes. Figure 5 shows the count of a selection of specific violent and non-violent charges in our sample. While the most common crimes are traffic related - and therefore non-violent - 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.[10]

We find the impact of heat on total crime is driven almost entirely by heat's impact on violent crime. As Figure 7 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-

[10] 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.

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.

The richness of our data allows us to examine how heat impacts detailed categories of violent and non-violent crimes as well. These detailed results indicate that the increase in crimes is driven not just by violent crimes, but specifically by increases in assaults (Figure 8). 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 aggravated assaults with a weapon increasing by between 10 and 20% on very hot days. 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.

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 and it is consistent with existing work on the impact of heat on crimes that either finds little impact on property crime (Ranson, 2014) or that heat's impact on property crimes is mediated by economic, rather than psychological, factors (Blakeslee et al., 2018). In Figure 9, 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. 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 use of force or violence. We examine these crimes separately and generally find no evidence of an impact of heat (Figure 10). Privacy violations, DUIs, and hit and runs all may increase slightly at temperatures over 90°F, but our estimates are all imprecise.

Our results indicate that the increase in crime on hotter days comes from an increase in violent crimes and, specifically, an increase in assaults. This is consistent with both the existing literature (Ranson, 2014; Heilmann et al., 2021; Harries et al., 1984) on heat and crimes and a broader psychological literature that suggests heat increases aggression and lowers psychological control. Our results support the hypothesis that heat's impacts on crime are driven primarily by heat's impact on an individual's psychological state rather than as a rational response to an expectation that, for example, police will be less active on hotter days. If heat operated through police activity, we would expect increases in both violent and non-violent crimes in response to changes in police action. That we find no evidence of heat increasing property crimes, which one may expect to be most closely tied to economic motivations for committing crime, suggests that this mechanism is not an important driver of the relationship between heat and crime, at least not in a setting like Texas. The fact that we find similar effects of cool days on violent and non-violent crimes, but null effects of heat on non-violent crimes, further supports this interpretation.

5.3 Heat and Reported Crime

In contrast to our use of arrests to examine the impact of heat on crime, much of the existing work on the relationship between heat and criminal activity uses reported crimes (Ranson, 2014; Heilmann et al., 2021; Jacob et al., 2007; Blakeslee et al., 2018; Bruederle et al., 2017). Arrest data have the advantage of capturing only crimes that result in actions later in the judicial process, as opposed to all incidents in which a reporting individual thought a crime might have occurred. These data suffer, however, from the disadvantage of capturing both the impact of heat on criminal activity and the impact of heat on police activity. An arrest is a two-sided process that depends on the activities of the defendant and the arresting officer. It is possible that heat impacts both participants in this interaction and existing work suggests that police behavior is impacted by higher temperatures (Obradovich et al., 2018). If heat induces police officers to be more aggressive or punitive, arrests might increase even if criminal activity remains unchanged. In that case, our measure of arrests would not capture the impact of heat on crime, but rather the impact of heat on police officers.

To try to separate the impact of heat on criminality and police action in driving our results in the arrest data, we examine how heat impacts reported crime in Houston. We can compare changes in reported crimes to changes in arrests for the same temperature shock in Houston to understand whether the increase we observe in arrests is driven more by increases in reported criminal activity or by increases in police aggression.

We find that arrests respond less to heat than reported crimes. In Table 2, we show how the average level of reported crimes and arrests differs across the sample covering Greater Houston. Across all types of crimes, reported crimes are on average about three times higher than arrests. This alone, however, does not indicate that heat has a larger impact on crimes than arrests. For that, we turn to Table 3. Here we report the results of the same Poisson fixed effects approach used in the analysis of overall arrest responsiveness to heat, but this time applied to the Houston PD reports data and the TDPS arrest data for the Greater Houston area. We find, in panel A, that heat's impact on reported crimes is roughly double that on arrests across all temperature bins above 80°F.

To more precisely estimate whether reported crimes increase on hotter days relative to arrests, we examine how the difference between reported crimes and arrests changes on hot days in Table 4. Here we subtract the number of arrests from the number of reported crimes. In column one, we report results using only arrests on the day of the reported crime. In column two, we also include all arrests on the following two days to account for possible delays in closing out an arrest. In both cases, hot days substantially increase the difference between reported crimes and arrests. On the hottest days, using the contemporaneous results, the difference increases by approximately 13%. In other words, on days above 100°F, for every additional arrest there are 1.13 more reported crimes.

We can further rule out that our results using arrest data are driven primarily by impacts on police by examining the pattern of effects across different crimes. Recall that we estimate no effects of heat on non-violent crimes, which include traffic violations. Traffic stops are an area in which police have significant discretion (Lichtenberg, 2002). If heat substantially increases police aggression and that is driving the increase in arrests we observe, one would expect to see larger impacts in crimes over which police have greater discretion. We do not find any evidence to support that hypothesis.[11]

[11] Existing work showing that police engage in fewer traffic stops on hotter days further suggests that police action declines on hot days and is additionally unlikely to be driving our results (Obradovich et al., 2018).

Further, our results are driven by crimes over which police have less discretion, namely assaults, homicides, and kidnapping. Police have less discretion in these crimes because they all require a victim, as opposed to traffic offenses which only require that a law be violated. It is possible that heat has differential effects on police action depending on the situation they are called to in ways that might lead to greater arrests for violent crimes. This might be the case if, for example, heat does not generally increase police aggression but makes officers more likely to escalate to an arrest conditional on observing violence. There is some evidence that police are less patient with defendants on hotter days and more likely to resort to violence (Vrij et al., 1994), which might support this hypothesis.[12] However, the magnitude of our results and the much larger impacts we observe on reported violent crimes make it difficult to explain our findings through increased police aggression.

There are two implications of these results. First, it does not appear that the increase in arrests we observe on hot days is primarily the result of changes in police activity. Heat may have small impacts on police aggression, but these impacts are not first order in explaining the increase in crimes or arrests that occurs on hotter days. In line with our results on the effects of heat on prosecutors and judges, we believe that working in pairs or teams reduces the effect of heat on police activity. Second, the increase in crime we estimate using arrest data appears to substantially underestimate the overall increase in crimes due to heat. This suggests that at least some of the increase in criminal activity that occurs on hot days is not accompanied by a corresponding reaction by the public safety and justice systems.

5.4 Differences in the Impact of Heat by Neighborhood Characteristics

The impact of heat on individuals, and their psychological state, is likely mediated through their built environment. 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 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.

[12]When we examine the impact of heat on the killing of civilians by police in Texas from 2013 to 2017 (the period for which we have data), we find no evidence that heat increases police killings.

We start with how the impact of heat varies by the age of the neighborhood housing stock. 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). We can and do examine whether housing age acts as a good proxy for the presence of air conditioning using CoreLogic data. In Figure A1, 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%.[13] 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, making air conditioning less effective in older houses.[14]

We find substantial impacts of heat in older, less air conditioned neighborhoods. In Table 5 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.[15] 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

[13]This is a far higher rate of AC penetration than for the country as a whole, where roughly 65% of houses had central air as of 2018.

[14]In Table A4 we show the impacts of heat in areas with above and below median levels of central air conditioning according to CoreLogic data. The pattern is consistent with the hypothesis that air conditioning is a main driver in the reduction of the impacts of heat: impacts in the areas with above median levels of central AC are 50%+ smaller than in areas 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.

[15]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.

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 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.[16]

We turn next to how the impact of heat on crime varies across high and low income neighborhoods. 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). 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 (t-stat: 313) relative to those above the median. Below median block groups are 11% less likely to have central air conditioning (t-stat: 390) and conditional on having air conditioning but not having central air they are 32% more likely to have a window unit (t-stat: 10). Housing quality along other dimensions may vary with income in ways that increase the impact of heat as well.[17] 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.

In Table 6, 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 6, columns 5-12) indicates that heat increases violent crimes across all income quartiles. The effect in the

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

[17]Existing work (Heilmann et al., 2021) has suggested that heat may have larger impacts in low income neighborhoods because of lower investments in activities like pre-school child education programs in these neighborhoods. Participation in these programs has been shown to reduce incarceration rates later in life (Reynolds et al., 2010; Baker et al., 2019) due to improvement in cognitive and non-cognitive skills that are associated with the programs. More generally, there is a clear relationship between investments in children's non-cognitive skills and family income (Fletcher and Wolfe, 2016). Lead exposure also varies systematically with neighborhood income (Galster and Sharkey, 2017) and childhood lead exposure has been shown to lead to criminality later in life (Nevin, 2007). Heilmann et al. (2021)'s proposed channel is a reduction in impulse control due to these lower levels of investment in childhood that make individuals in these neighborhoods more susceptible to the impacts of heat.

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 reports 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.[18] 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 wealth 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.[19]

We next attempt to determine whether income or housing age is a more important mediator of the impact of heat on crime. Doing so can help to 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 (Heilmann et al., 2021). Neighborhood age and income are correlated in our sample ($\rho \approx 0.3$).[20] 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. To deal with the imprecision that comes from having smaller cell sizes, we widen our temperature bins from five degrees to ten degrees.

We present results for heat's impact on arrests for violent crimes in Table 7 and leave results on total crime and nonviolent crime for Tables A5 and A6. In all three cases, the pattern is the same. On average, we observe the largest impacts in older neighborhoods within each income quartile. There is no statistical difference between the impacts of a day above 90°F on violent crimes in

[18] 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.

[19] 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 A7. 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.

[20] Moving from the median to the 90^{th} percentile of the neighborhood age distribution increases median income by about 25% or moves one from the median of the income distribution to roughly the 65^{th} percentile.

neighborhoods with older housing stock across all four income quartiles. 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. This suggests 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 appears to be driven by the correlation between neighborhood income and housing quality.

Finally, we look at whether heat leads to differential effects on arrests in rural and urban neighborhoods. 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.The resulting urban and rural block groups are mapped in Figure A2. 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 11 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.

We also look at 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 8). 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. We also 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 A8).[21]

5.5 Impact of Heat on Crimes by Race and Ethnicity

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

Figure 12 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

[21] 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.

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.

5.6 Policy Evaluation: Open-Carry and Heat

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.[22]

As a consequence, 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 9).[23] The range in effects is 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

[22] It may have also made it more likely for owners of guns without permits to carry their guns in the expectation that police would assume anyone carrying a weapon had a permit.

[23] To be clear, gun charges are their own category of charges (e.g., "brandishing a firearm") and not a subset of assaults or aggravated assaults.

were particularly likely to be impacted by the law change.[24] 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.

6 Results II: Criminal Justice Outcomes and Heat

We turn now to an examination of how the cases of those arrested on hot days proceed through the judicial system. A significant advantage of our data compared to much of the data used in previous examinations of the impact of heat on crime is that we can observe the outcome of every step of the judicial process - from arrest to prosecution to trial - for a given case. We take advantage of the comprehensive scope of our data to examine whether individuals arrested on hot days experience different outcomes than those arrested on cooler days.

We begin by examining whether being arrested on a hot day changes the probability of charge dismissal or of conviction.[25] Figure 13 shows the percentage change in dismissals and convictions when the arrest associated with the case occurs on a day in each bin of the temperature distribution. Temperature appears to have a larger impact on dismissals than convictions. A day in the 95°-100°F bin leads to roughly 8% more dismissals, but only roughly 3% more convictions. The p-value

[24] The list of these specific charges is included in Table A9.

[25] Dismissal and conviction are not the only outcomes in our data – defendants can also be found not guilty or they can be convicted of a lesser charge. Convictions and dismissals, however, account for more than 95% of the outcomes.

of the difference between these estimates is <0.01.

Total arrests increase on hot days, but by less than the percentage increase in dismissals. That suggests a larger share of the additional arrests on hot days result in dismissals than convictions. To examine this directly, we estimate a fixed effects linear probability model with an indicator for whether a case results in a dismissal or a conviction as the outcome. Figure 14 shows that the share of cases resulting in dismissals does appear to rise on hot days, while the share resulting in convictions falls. The difference between dismissal and conviction rates begins to appear at temperatures above 75°F and continues to diverge as temperatures increase. At all temperatures above 80°F, the difference in the change in the share resulting in a dismissal is significantly different from the change in the share resulting in a conviction. We also examine how convictions and dismissals change on hot days for White, Black and Hispanic defendants. We do not find evidence that the impact varies by race or ethnicity (Table A10).

What is driving the change in dismissals? One possibility is that different crimes have different rates of dismissal and conviction and heat impacts those crimes differently. We have already show that violent crimes increase substantially on hot days while non-violent crimes are essentially unchanged. This implies that the violent crime share of arrests is higher on hot days than on less hot days. If violent crimes are dismissed (or convicted) at higher (lower) rates than non-violent crimes, we might see this pattern simply because of the change in the type of crimes that occur on hot days. As we show in Table A11, violent crimes are in fact dismissed at higher rates and convicted at lower rates than non-violent crimes. To what extent does this drive our results?

Our estimates suggest that on days greater than 100°F, the share of arrests for violent crimes as a percent of total arrests increases from 15% to 17%. If we assume that the share of violent crimes that is dismissed remains constant across hotter and cooler days, that implies a mechanical 0.65 percentage point increase in dismissals due to the change in the types of crimes that occur on hot days. We observe an increase in dismissal rates of 1.01 percentage points on hotter days relative to cooler days. So it appears that the mechanical change in dismissals can explain roughly 65% of the increase that we observe. The implied mechanical decline in the convictions rate, on the other hand, is roughly 100% of the observed decline in convictions. The change in convictions is thus due primarily to the changing make-up of crimes on hot days rather than the changing behavior of prosecutors or judges. The implied mechanical changes are based, however, on the assumption that the rate at which violent crimes are convicted or dismissed remains constant across arrests on hot and cold days. Our evidence supports this assumption, but it is difficult to test its validity.[26]

Taken together, our results suggest that a greater share of arrests on hot days result in dismissals, relative to arrests that occur on cooler days. Why this occurs is not obvious. The change in convictions may be due to the change in the relative share of the types of crimes that are committed on hotter and cooler days. This mechanical effect, however, does not explain the total difference in dismissals. The difference that remains after accounting for the mechanical effect may be due to police making more arrests on the margin on hot days, ones that prosecutors cannot successfully prosecute. This could result from police officers being aggravated by heat in ways that increase their proclivity to arrest when an arrest is not warranted or to arrest preemptively, to diffuse a potentially violent situation.

7 Results III: How Heat Affects Prosecutors and Judges

If heat increases crime by reducing psychological control, impacting mood, or changing emotional affect, there is no reason to believe that its impacts will be limited to criminal defendants. Rather, it is likely that heat also impacts prosecutors and judges. While prosecutors and judges likely conduct most of their business in air conditioned buildings, there are still numerous channels through which heat could impact their decisions. Both judges and prosecutors, for example, may be exposed to heat before or during their commute. This exposure may exert a persistent impact on them throughout the day. Existing work has shown that seemingly unrelated events occurring days prior to a trial can exert a persistent influence on judge decisions (Eren and Mocan, 2018). Heat may also influence judge or prosecutor behavior due to exposure during breaks or by preventing them from going outside during a break in order to avoid exposure. Thus, even though judges and prosecutors work in climate controlled environments, heat may play a role in their decision-making. Existing work looking specifically at judges operating in climate controlled environments throughout the United States supports this conclusion, finding that immigration judges grant fewer

[26]We also examine whether the increase in dismissals is driven by a potential increase in arrests of first-time offenders on hot days and judges or prosecutors exhibiting leniency toward these first-time offenders. We find no evidence that hot days increase the number of first-time offenders or that these cases are driving the increase in dismissals on hot days.

asylum requests when the case is heard on a hot day (Heyes and Saberian, 2019).[27]

We note an important distinction between the decision process of prosecutors and judges, however.[28] Prosecutors generally work in a team to make determinations on the charges they want to bring in a case and this process can take days. Further, in many district attorney offices and attorney general offices the charging decision goes through a multi-step process, where junior attorneys make a recommendation and senior attorneys make a final decision. This spreads out the decision-making process over several days and several individuals, reducing the cognitive load on any single person in ways that may mitigate the role of heat. In contrast, judges make decisions about most cases by themselves, on a single day, and under pressure to move through cases quickly.

To analyze whether heat on the day of the decision influences the prosecutor and/or judge's decision in a given case, we work with the date on which each makes their decision. We take a similar empirical approach to the previous section, but we shift our unit of analysis to the prosecutor offices and the courts in which cases are decided. We link these to the counties according to Texas data on where each prosecutor or court is based, in order to assign daily temperatures. In keeping with Heyes and Saberian (2019), we focus on the mean temperature, rather than the daily max, because mean temperature is more likely to capture high temperatures during the morning commute. Maximum temperature, in contrast, generally captures the temperature during the peak of the afternoon when judges and prosecutors are likely to be least exposed, since we believe exposure during the commute to be a major driver of the relationship.[29] Because we focus on mean temperature, our highest temperature bin contains all days above 90°F, as days with a mean temperature higher than 95°F are rare in our data. In all judge and prosecutor regressions, we also control for the total number of cases that the prosecutor filed or judge heard on that day to account for any instances in which having to work through a wave of cases might influence their behavior.

7.1 Prosecutors

Prosecutors have a great deal of discretion in the U.S. legal system (Sklansky, 2018). They can choose to drop charges, not proceed with charges for lack of evidence, or change charges against

[27] Kahn and Li (2020) find that heat does not appear to have a meaningful impact on the productivity of judges in China. However, the outcome measure is the time it takes judges to make a decision on a case, rather than the decision itself.

[28] These observations are based on discussions with practicing attorneys.

[29] Using max temperature, however, produces qualitatively similar results to using mean temperature.

a defendant. Our data record information about these decisions. Specifically, we observe whether prosecutors chose not to pursue charges, whether charges were changed by the prosecutor, and in what direction they were changed. We classify any charges that the prosecutor did not seek, for any reason, as dropped.[30] We classify as released cases where the prosecutor released the defendant prior to trial. Charges that were changed we code as up or down coded. These are distinct from decisions made by courts. Namely, if a prosecutor pursues a charge but the court dismisses it or finds the defendant not guilty we code those as dismissed or not guilty charges. Cases where the court finds the defendant guilty we code as a conviction or a conviction on a lesser charge.

When we evaluate prosecutorial, and court, discretion we only consider those cases that have reached each stage of the judicial process. For example, the share of cases where charges are added by prosecutors are calculated as the number of cases with added charges as a share of the number of cases that prosecutors choose to pursue.

We examine two different aspects of prosecutor decisions to test the hypothesis that high temperatures influence their decisions. First, we consider whether prosecutors change the number of cases they choose to drop or release without prosecution on hot days. Second, we examine whether the prosecutor is more likely to add additional charges beyond the arresting charges and, conditional on adding charges, if they add more additional charges on hot days. Our data indicate all of the charges the defendant faced after their arrest. But they also indicate whether the prosecutor specifically added to those charges - distinct from whether or not the prosecutor increased the level of the arrested charge. For example, adding a resisting arrest charge to a defendant who was arrested for being drunk and disorderly.

We fail to find evidence that heat impacts prosecutor decisions regarding whether to drop a case. We show in Table 10 that prosecutors do not appear to release defendants or drop charges with any greater or lesser frequency on hot days. Our point estimates suggest that they may be more likely to add charges on hotter days, but these estimates are very imprecise, with standard errors of the same magnitude as the point estimates. We find that, conditional on adding charges, prosecutors may add more charges on hot days, but our point estimate is only weakly significant and only a small share (roughly 2.5%) of cases in our data ultimately see additional charges being

[30]Our data include multiple reasons for why charges were not sought. We classify cases with "No Bill", "Agency dropped charge", "Rejected charge due to diversion", "Withdrawn by complainant", and "Prosecutor reject charge" as dropped charges.

added. When we examine these outcomes separately for White, Black, and Hispanic defendants we find little to no evidence that heat impacts prosecutors' treatment of defendants of different races or ethnicities. Table A12 show that our estimates for how heat impacts prosecutors' decisions to release defendants early, does not vary across race or ethnicity. In Table A13, we show that prosecutors may be more likely to add charges to Black defendants' charges on hotter days, but our estimates also suggest that conditional on having added charges, White and Hispanic defendants have more additional charges than Black defendants. While meriting future work to examine this question more closely, our results do not suggest that heat leads to differential prosecutorial decisions based on the race or ethnicity of the defendant.

Overall, our results suggest that heat does not exert a meaningful influence on prosecutor decisions. This may be because of the more diffuse decision making process in most prosecutor's offices, making temperature on the day of the decision less relevant for the process. It is consistent with existing work on prosecutor bias that suggests prosecutors may be biased in specific circumstances (e.g., male prosecutors prosecuting female defendants (Didwania, 2018)), but not on average. This highlights a limitation of our data - we do not know which prosecutor in a prosecutor's office pursued a given case and how the process unfolded - and leaves open the possibility that more refined data might in fact show the impacts of heat on decision making in specific contexts.

7.2 Judges

Our data and setting allow us to test a wider range of hypotheses around the impact of heat on judges than Heyes and Saberian (2019). There is a greater variety of outcomes for defendants in a criminal case as well as a range of actions the judge can take in addition to determining guilt or innocence. We measure two different judicial outcomes and determine whether judges are more punitive when the case is heard on a hotter day.[31]

First, we assess whether judges making decisions on hotter days are more or less likely to convict or dismiss a defendant. Our data records four outcomes indicating guilt or innocence: "convicted," "convicted of a lesser charge," "dismissed," and "acquitted." Convictions and dismissals account for 94% of the cases for which a determination of guilt has been made and so we focus our analysis

[31] In all of these analyses we do not control for the temperature on the day of the arrest. The correlation between the temperature on the day of arrest and the day of the court's decision is 0.11. This is likely due to a sizeable delay between the date of arrest and the date of the court's decision. On average, in our data, that difference is 5 months.

on these.

Second, we consider the punishments issued by the courts. We have data on the length of the sentence, the length of probation, and the amount of any fines issued.[32] We do not have information on the types of punishment a given charge is eligible for and so when we analyze punishments we only consider those cases for which the punishment data are greater than zero. In all analyses we control for the total number of cases that a judge hears on a given day to address concerns that there may be correlation between the temperature on a given day and the number of cases the judge hears.

Our results indicate that courts consistently behave in ways that are less favorable to defendants when the decisions are made on hotter days. Table 11 shows in columns 1 and 2 the change in convictions and dismissals for a day above 90°F. Our estimate for convictions is imprecise and not significant, but indicates a 90°F day increases convictions by about 1%.[33] Dismissals, however, fall by just under 5% on a day with mean temperature above 90°F.

Courts appear to issue more severe punishments on hotter days relative to cooler days. The length of confinement increases by approximately 6.5% when the decision is made on a day with mean temperature above 90°F. Fines also increase on hot days, by approximately 4%, but we do not observe changes in the length of probation.[34]

As with prosecutors and police, heat does not appear to impact judges' decisions differentially based on the defendant's race or ethnicity. In Tables A14-A15, we show that hot days impact judges' decisions about conviction or dismissal similarly for White, Black and Hispanic defendants. Nor does heat impact the length of sentence or amount of the fines they issue differently for White, Black, or Hispanic defendants.

Taken together, these effects suggest that outdoor temperatures do impact the decisions made by judges. Judges become less willing to dismiss cases or reduce the charges faced by defendants and issue more severe sentences on hotter days. This is consistent with the hypothesis that heat

[32] Fines are separate from court costs that defendants are ordered to repay.

[33] Calculated as 0.635/68.97. That is the β estimate of the percentage point change in convictions due to a day above 90°F (0.635) as a percent of the mean conviction rate (68.97) reported in the bottom of the table.

[34] The number of cases that result in a sentencing decision or a court fine is relatively small. Figure A3 shows the results of a randomization inference test to examine whether our estimates of the impact of days above 90°F on sentence length and fines are simply due to random chance in which cases happen to be decided on the hottest days. The p-value from the randomization inference test in both cases suggests that our results are significant and not due to random chance in which cases are decided on hot days.

increases cognitive and emotional stress in ways that has consequences for the outcome of cognitively intensive tasks. These results indicate that these effects can have meaningful effects on performance even in settings without significant physical labor and with high AC penetration.

8 What Can We Expect From Climate Change?

Climate change, even under the most optimistic scenarios (see Figure A5), 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. 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., 2017). 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 block group in our data, which allows us to examine the regressivity of future exposure to temperature accounting 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. (2017). 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 (e.g., Heutel et al. (2014)) 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.

Building on our results in Section 5.4, we measure adaptation in several different ways. Our results 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 (e.g., 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 (e.g., 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 1.[35]

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

[35] Past work has found that historic exposure to temperature is a meaningful predictor of adaptation (Heutel et al., 2014). 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 A16). This may be due to the fact that existing evidence for hotter areas being more adapted comes from examinations across the entire United States. By a standard of heat exposure measured across all of the United States, all of Texas would be considered very exposed. Given the high level of average exposure across all of Texas, it may be that other determinants of adaptation are more important than historic exposure within Texas.

changes in temperatures in every year from 2030 to 2050 relative to the 2000-2010 average, times the marginal effect in each bin according 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 15, 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 15 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 A17).

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 A17).

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 A18, 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.[36] As we show in Panel C of Figure 15, 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 15), 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 A7). Under this scenario, all block groups have new housing by 2050 and the overwhelming majority are in the highest income bin (Figure A18). 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.

Finally, we take advantage of our ability to estimate not only heat's impact on arrests but also its impact on the likelihood of conviction to examine how future climate change will change the probability, relative to today, that an average Texan will be convicted of a crime in a given year. This is separate from what we estimate above, which is the impact of future climate change on the total number of arrests. In examining climate change's impact on the probability of conviction we assume that conviction depends both on being arrested for a crime and the rate at which arrests become convictions, both of which are impacted by the heat.

We begin by calculating the change, based on changing temperatures, in the probability that an individual will be arrested for a crime over the course of a typical year. We combine this with our data on how conviction rates vary based on the temperature on the day of the arrest. In this exercise, we do not explicitly account for adaptation because our estimates of the impact of heat

[36]This is in contrast to the relative impact of hot and cold days on many other outcomes. For example, in the context of mortality and education, reducing cold days tends to be beneficial.

on conviction rates are not inclusive of adaptation. See Appendix 2 for full details behind this calculation.[37]

Figure 16 shows the results of this exercise. Unsurprisingly, the probabilities reflect the pattern of our point estimates, with cooler days reducing the probability of arrests and convictions and warmer days increasing it. Given the number of days that Texas typically experiences over 100°F every year, Texans are 50% more likely to be arrested and convicted of a crime than if those days were all replaced by 65° days. We integrate the area under the implied curve to determine the total change in the probability of being arrested and convicted of a crime relative to the scenario in which every day of the year is 65°F. We then examine how this probability changes if Texas, given current levels of adaptation, experienced the distribution of days across the temperature bins expected under the RCP6.0 scenario. We find that the RCP6.0 scenario increases the annual probability of arrest and conviction by 12% relative to today's temperature distribution. This increase occurs because there are substantially more days over 100°F and substantially fewer days below 40°F under the RCP6.0 scenario relative to today's distribution.

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. 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 dis-

[37] In a separate analysis, we account for the temperature on the day of the trial as well, but find that it has a limited effect on our outcomes and so omit it here.

tribution 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 (e.g., workplace safety), this will not always be the case.

9 Conclusion

We study how the negative effects of heat on cognition, mood, and emotional state in turn affect criminal behavior by regular citizens and the decision making process of police officers, prosecutors, and judges. We find that heat significantly increases arrests, especially for violent crimes. Heat has a larger effect on reported crimes than on arrests and does not appear to significantly affect police behavior. 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.

Heat also affects the judicial process directly. Judges ruling on hot days are less likely to dismiss cases and, conditional on conviction, more likely to hand down harsher sentences. Prosecutors, however, do not appear to change the way they file charges when they do so on hot days. Though both judges and prosecutors work in climate controlled environments, prosecutors work on charges over several days and in teams, while judges decide on sentence severity alone and often under significant time pressure. Convictions, determined by juries, appear unaffected by heat on the day of the decision. These results suggest that teamwork could play an important role in reducing the adverse effects of heat on decision-making.

Our findings show that universal climate control is not a panacea when it comes to mediating the negative 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%, but on current trends adaptation will not eliminate them. 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 and encourage more team-based work as a check on individual decision-making can 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%.

10 Tables and Figures

10.1 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: Houston sample summary statistics

	Mean	SD	Min	Max
Houston police department incident data				
Total crimes	0.49	0.90	0	33
Violent crimes	0.05	0.22	0	5
Non-violent crimes	0.36	0.75	0	32
TDPS arrest data				
Total crimes	0.16	0.49	0	33
Violent crimes	0.02	0.16	0	16
Non-violent crimes	0.08	0.31	0	25

NOTES: All crime counts are aggregated to the tract level. We limit the sample in the Texas Department of Public Safety (TDPS) data to those tracts for which we have data on Houston police department incidents. Statistics are daily values across Houston tracts in the 2010-2017 time period.

Table 3: Impact of heat on reported crimes and arrests in Houston

	All crime	Violent crime	Non-violent crime
(A) Houston PD data			
T above 100F	0.088***	0.147***	0.090***
	(0.016)	(0.052)	(0.018)
T 95-100F	0.080***	0.226***	0.062***
	(0.009)	(0.030)	(0.011)
T 90-95F	0.062***	0.214***	0.045***
	(0.008)	(0.029)	(0.010)
T 85-90F	0.049***	0.184***	0.036***
	(0.008)	(0.026)	(0.009)
T 80-85F	0.048***	0.137***	0.039***
	(0.007)	(0.023)	(0.009)
T 75-80F	0.037***	0.090***	0.034***
	(0.007)	(0.024)	(0.008)
N	1,837,938	1,712,292	1,829,172
(B) TDPS data			
T above 100F	0.023	0.078	-0.013
	(0.026)	(0.066)	(0.031)
T 95-100F	0.030**	0.092**	0.000
	(0.015)	(0.037)	(0.018)
T 90-95F	0.051***	0.095***	0.029*
	(0.013)	(0.032)	(0.016)
T 85-90F	0.053***	0.099***	0.029*
	(0.013)	(0.031)	(0.015)
T 80-85F	0.034***	0.094***	0.002
	(0.011)	(0.026)	(0.014)
T 75-80F	0.027**	0.043*	0.010
	(0.010)	(0.025)	(0.013)
N	3,079,788	3,071,022	3,079,788
Fixed Effects:			
Tract	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. Houston PD data measure the number of crimes reported to the Houston Police Department. Not all of these result in an arrest. TDPS data report the number of arrests reported to the Texas Department of Public Safety. In all cases, we aggregate the count of incidents (Houston PD) data or arrests (TDPS data) to the tract-day level and conduct analysis at that level of aggregation. We restrict the sample to those tracts that contain at least one crime reported to the Houston PD in all regressions. The sample in all cases is a balanced panel of these tracts at the daily level from 2010 to 2017. Errors are clustered at the tract level and are reported in parentheses. All regressions are weighted by the total population in each tract-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. *p=0.1, **p=0.05,***p=0.01.

TABLE 4: Impact of heat on the difference in reported crimes and arrests in Houston

	Contemporaneous arrests	3-day pooled arrests
T above 100F	0.045***	0.047***
	(0.010)	(0.012)
T 95-100F	0.034***	0.040***
	(0.005)	(0.007)
T 90-95F	0.022***	0.023***
	(0.005)	(0.007)
T 85-90F	0.016***	0.021***
	(0.004)	(0.006)
T 80-85F	0.018***	0.020***
	(0.004)	(0.006)
T 75-80F	0.015***	0.015***
	(0.004)	(0.005)
N	1,840,860	1,839,600
Outcome mean, T60-65	0.33	0.03
Fixed Effects:		
Tract	Yes	Yes
Month	Yes	Yes
Year	Yes	Yes
DOW	Yes	Yes

NOTES: All columns report the results of a linear fixed effects specification. We estimate the impact of a hot day on the difference between the number of incidents reported to the Houston Police Department (Houston PD) and the number of arrests reported to the Texas Department of Public Safety (TDPS). In all cases we aggregate the count of incidents (Houston PD) data or arrests (TDPS data) to the tract-day level and conduct analysis at that level of aggregation. The sample in all cases is a balanced panel of tracts that contain at least one Houston PD crime report at the daily level from 2010 to 2017. In column 2, we pool arrests across the day of interest and the following two days. Errors are clustered at the tract level and are reported in parentheses. All regressions are weighted by the total population in each tract-year. All regressions include the full set of precipitation bins and temperature bins. Coefficients report the raw change in the difference between incidents and arrests for a day in a given temperature bin relative to the omitted 60-65°F bin. Postive differences indicate more incidents than arrests. 100× the coefficient estimates divided by the mean reported at the bottom of the table indicates the percent change in the difference on days in each bin relative to a day in the omitted 60-65°F bin. *p=0.1, **p=0.05,***p=0.01.

Table 5: 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. *p=0.1, **p=0.05,***p=0.01.

TABLE 6: 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. *p=0.1, **p=0.05,***p=0.01.

Table 7: 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. *p=0.1, **p=0.05,***p=0.01.

Table 8: 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. *p=0.1, **p=0.05, ***p=0.01.

Table 9: 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. *p=0.1, **p=0.05,***p=0.01. Compiled 13 Jul 2021.

Table 10: Impact of heat on day of prosecution action on filed charges

	Dropped	Released	Added charge	Number of added charges
T above 90F	1.613	-0.000	0.278	0.158**
	(2.015)	(0.005)	(0.274)	(0.076)
T 85-90F	0.300	-0.002	0.020	0.073
	(1.649)	(0.003)	(0.167)	(0.077)
T 80-85F	-0.355	-0.004	-0.086	-0.058*
	(1.269)	(0.003)	(0.093)	(0.031)
N	1,992,677	1,992,677	1,992,677	51,321
Outcome mean:	35.18	0.01	2.58	1.42
Fixed Effects:				
County	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the prosecutor level. Outcome for charges is specified in column headings. All regressions are linear probability panel fixed effects. All include controls for dew point, minimum vapor pressure deficit, and the gender, race, and ethnicity of the defendant. All regressions are weighted by the total cases the prosecutor tries in our sample. "Dropped" refers to cases that are coded in the data as "No Bill," "Agency drop charge," "Pros. reject charge," "Withdrawn by complainant," and "Pros. rejcted charge due to diversion." "Released" refers to cases that are coded in the data as "Released w/o Pros" and are not coded as "Dropped." *p=0.1, **p=0.05,***p=0.01. Compiled 8 Jul 2021.

Table 11: Impact of heat on courts

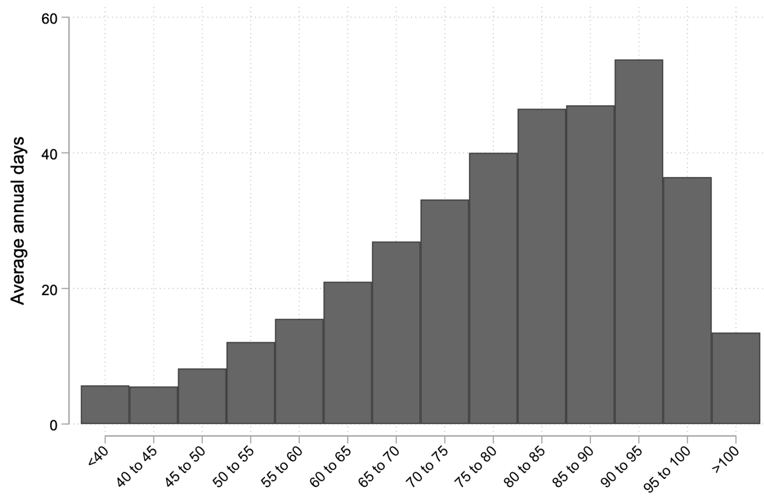
	Outcomes		Punishments	
	Conviction	Dismissal	Confinement	Fines
T above 90F	0.609	-1.216**	0.065**	0.040**
	(0.464)	(0.588)	(0.030)	(0.018)
T 85-90F	-0.195	0.030	0.016	-0.012
	(0.242)	(0.304)	(0.016)	(0.010)
T 80-85F	-0.096	0.128	0.025	-0.007
	(0.204)	(0.258)	(0.015)	(0.010)
N	1,140,602	1,140,602	763,199	1,071,518
Outcome mean,:	69.12	29.45	578.71	546.83
Fixed Effects:				
County	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the court level and shown in parentheses. Outcomes are specified in the column headings. Conviction indicates the defendant was convicted of the original charge. Dismissal indicates the charge was dismissed. In columns 1 and 2, outcomes are measured as the percentage of cases with that result. For example, 29.45% of cases are dismissed. Coefficients indicate the percentage point increase in the outcome for an additional day in each bin. In columns 3 and 4, Confinement and Fines outcomes are logged so that coefficients should be interpreted as percentage changes from the non-logged mean presented in the middle of the table. Confinement is measured in days, fines are measured in dollars. All regressions are linear panel fixed effects. We include the full set of temperature and precipitation bins in all regressions, but suppress some coefficients for readability. All regressions include controls for the total number of cases heard in the day, dew point, and vapor pressure deficit minimum. *p=0.1, **p=0.05,***p=0.01.

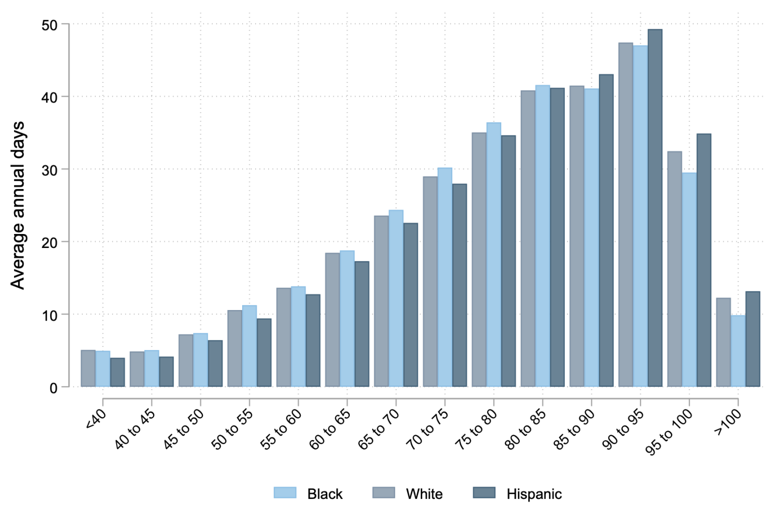
10.2 Figures

Figure 1: Temperature distributions

(a) Full sample



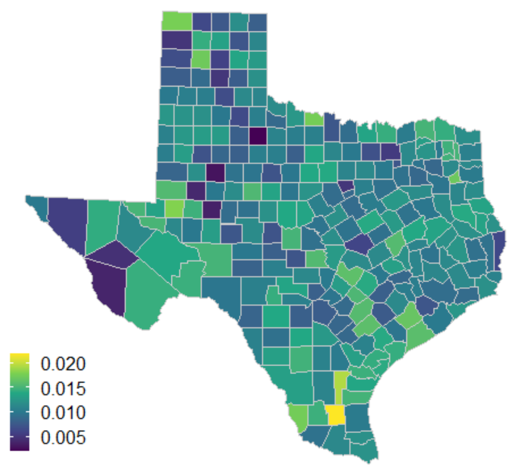
(b) Temperature distribution by race



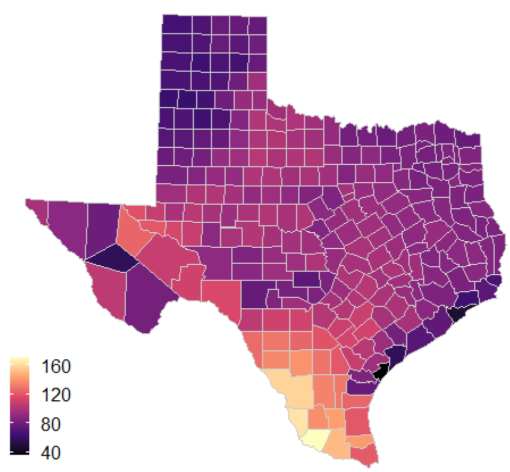
Notes: Panel A plots the distribution of days in each temperature bin averaged across all counties and years in the sample. Panel B reports the same, but shows distributions separately by race and ethnicity.

Figure 2: Maps of arrests and heat across Texas

(a) Average daily arrests



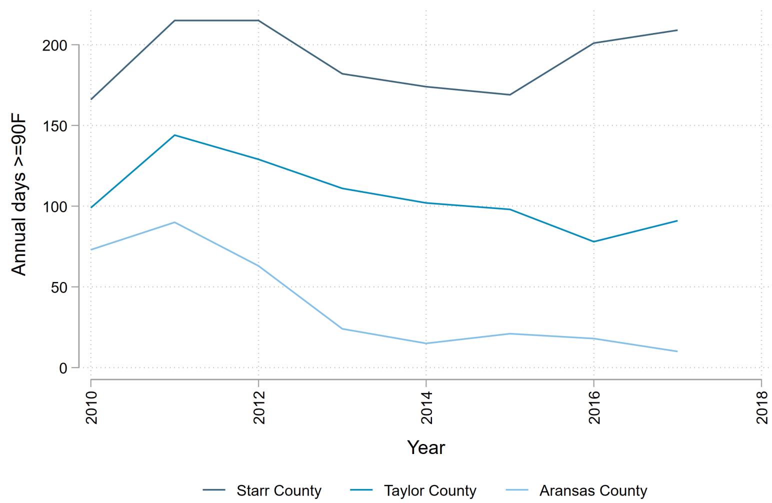
(b) Days > 90°F



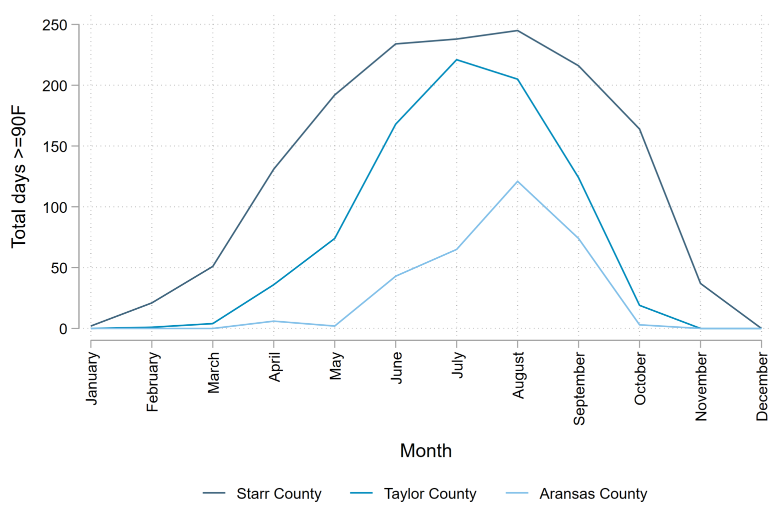
Notes: Panel A reports the average daily number of arrests per capita in each Texas county from 2010 to 2017. Panel B reports the average number of > 90°F days by county per year over the same time period.

Figure 3: Hot day distributions

(a) Annual hot days



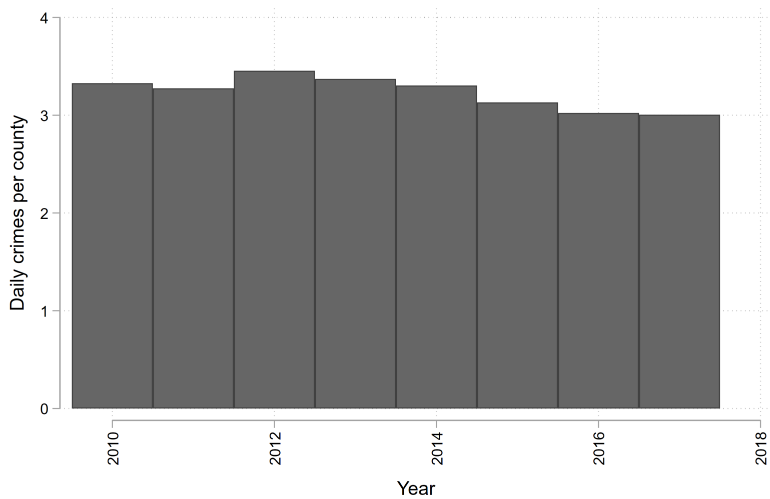
(b) Monthly hot days



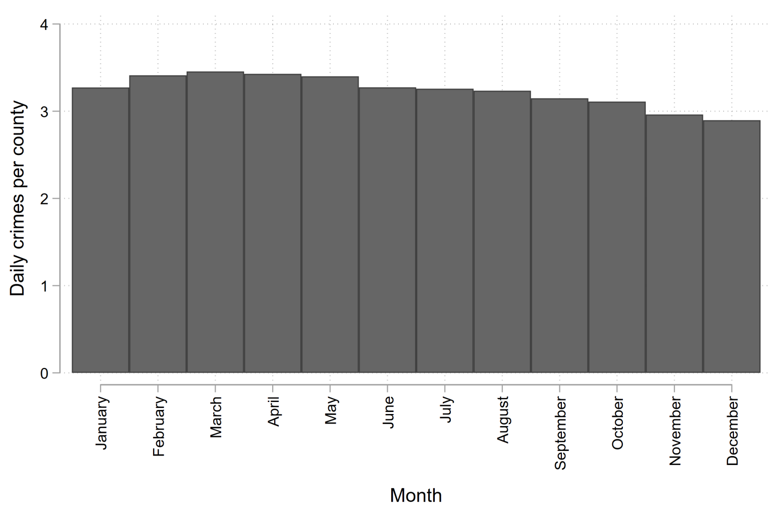
Notes: Panel A shows the trend in days > 90°F in three selected counties from each tercile of the distribution of the average number of hot days over the sample. Panel B shows the trend on average by month for the same counties to illustrate that there is significant variation across counties in our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

Figure 4: Total arrests

(a) Annual arrests

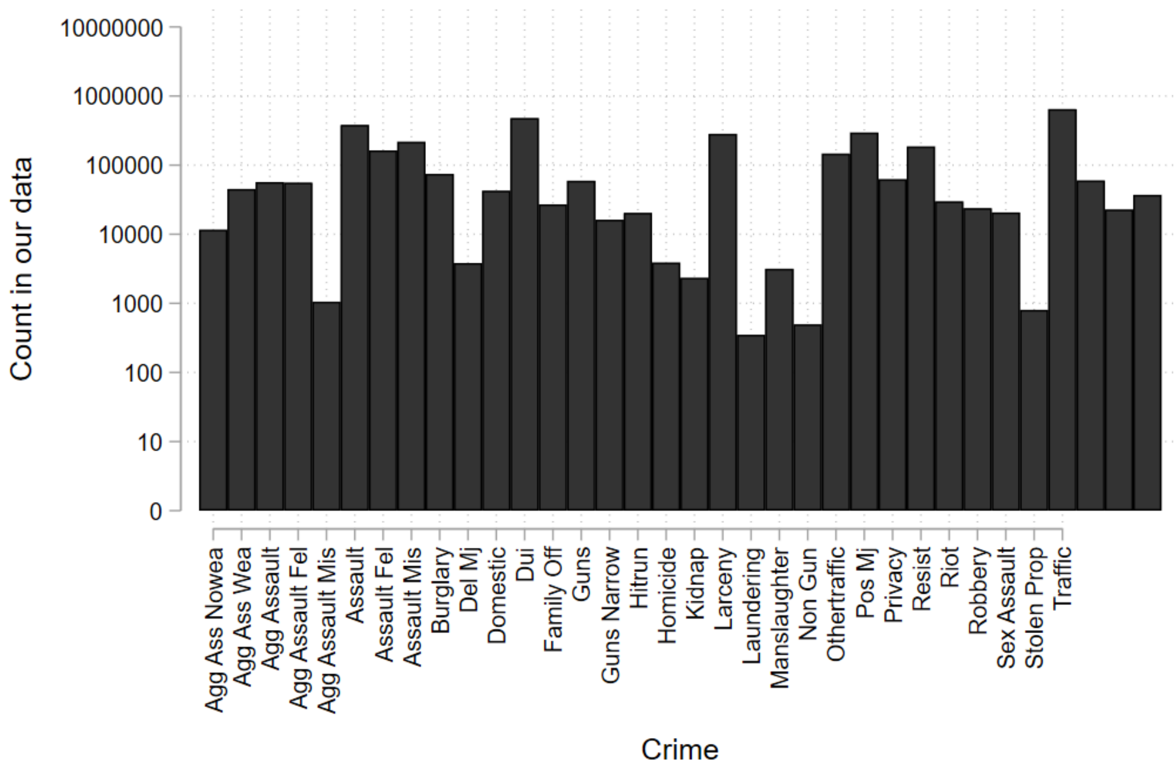


(b) Monthly arrests



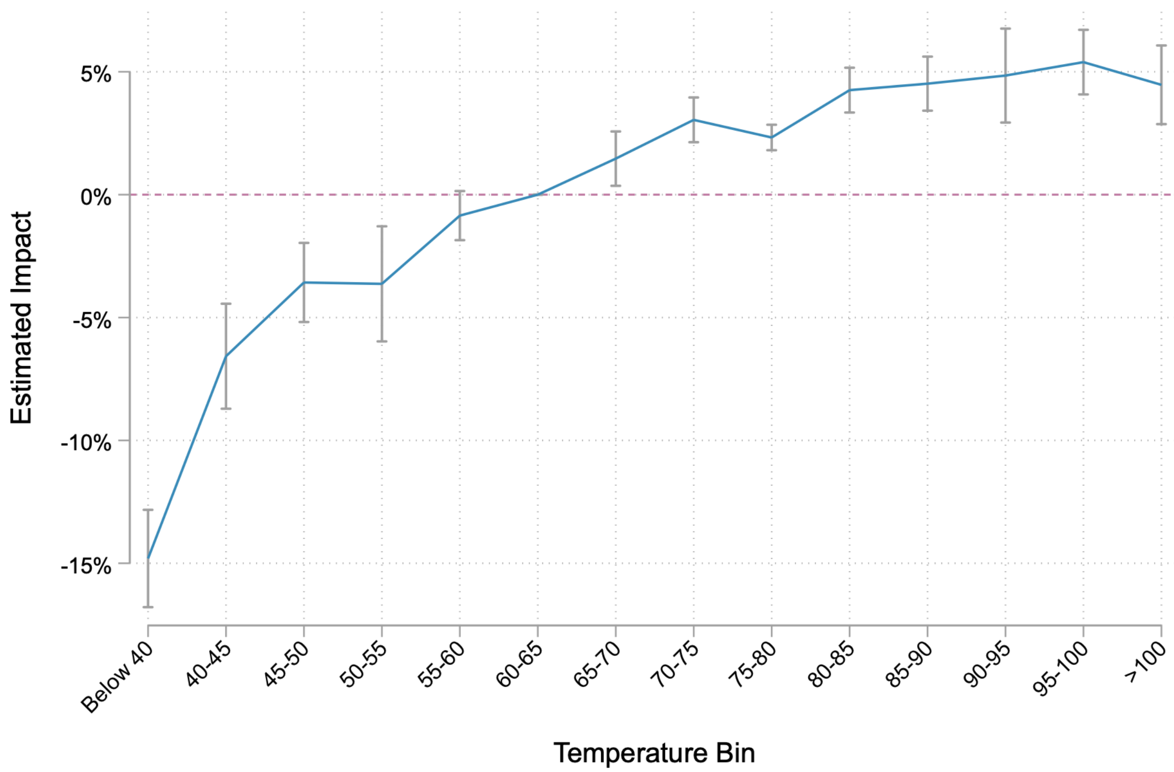
Notes: Panel A shows the average daily arrests in each year, averaging across all Texas counties. Panel B shows the monthly average across all the counties and years in our sample.

FIGURE 5: Crime counts



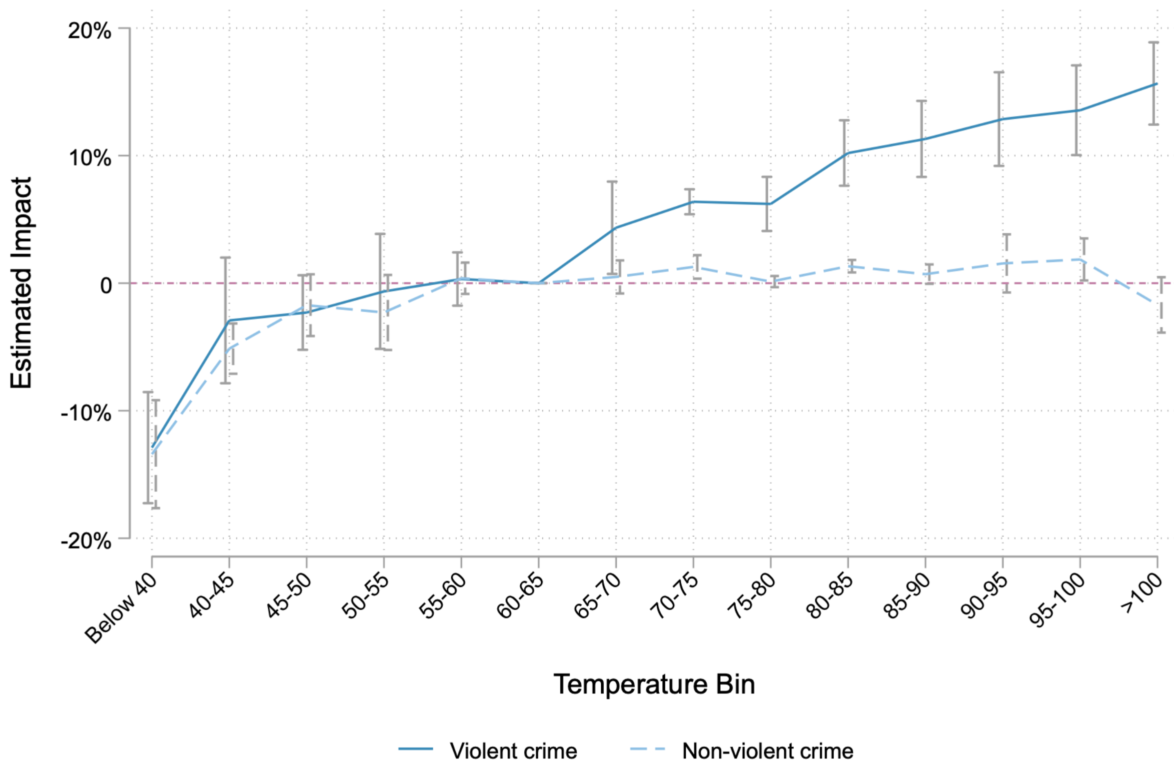
NOTES: Raw count of arrests across our full sample (2010-2017) by type of crime, prior to collapsing to block groups and counties. Note the log scale.

Figure 6: 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.

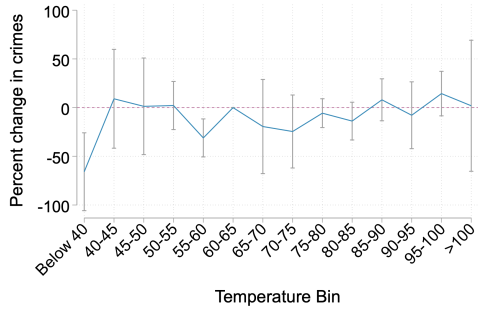
Figure 7: Effect of heat on violent and non-violent crime



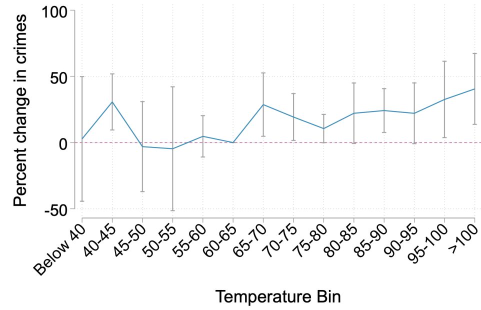
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60 - 65°F$ day. Model includes county, year, month, and day of week fixed effects. We control 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 8: Heat's impact on violent crimes

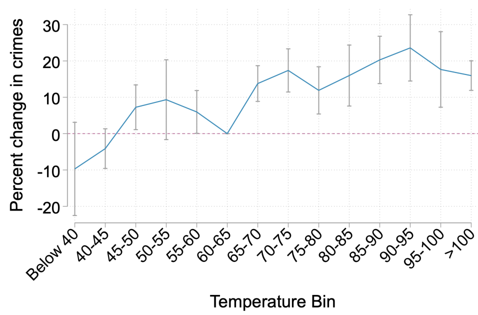
(a) Manslaughter



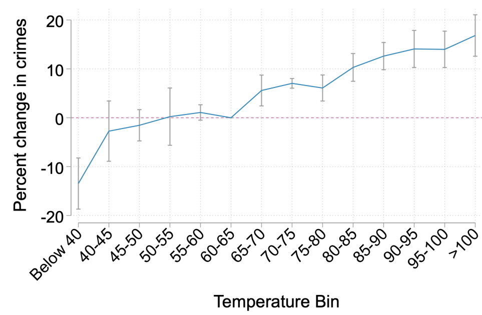
(b) Homicide



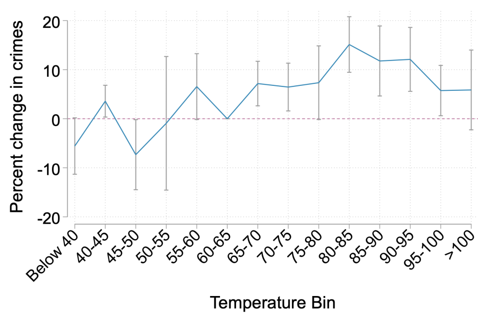
(c) Aggravated assault



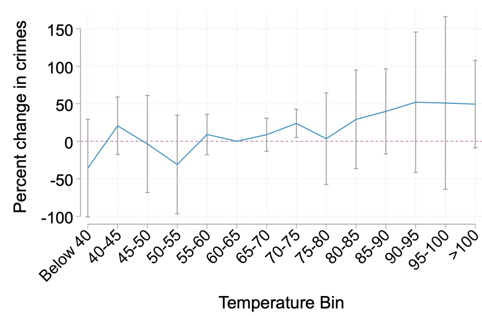
(d) Assault



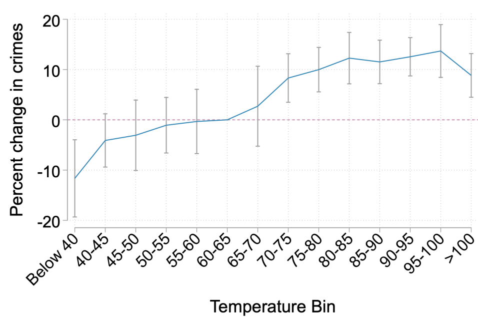
(e) Domestic assault



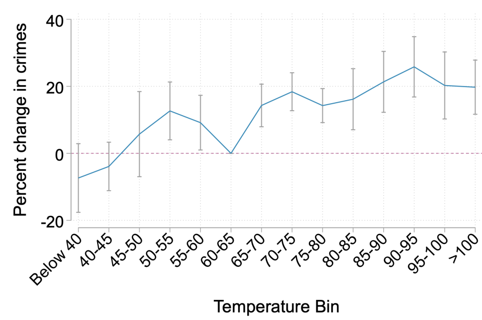
(f) Kidnapping



(g) Weapons crimes



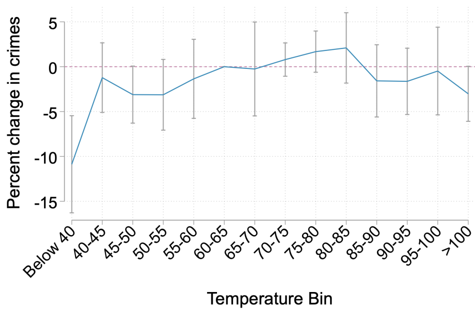
(h) Agg. assault, weapon



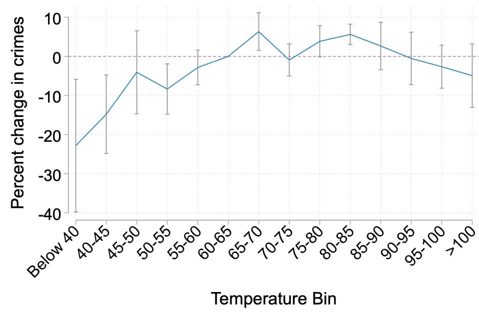
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control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

Figure 9: Heat's impact on non-violent crimes

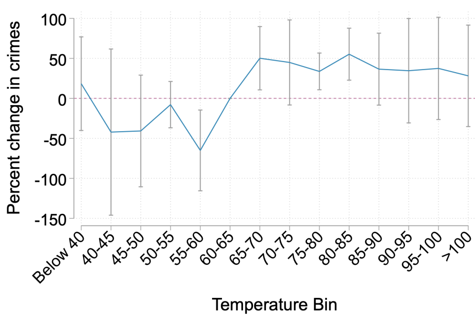
(a) Larceny



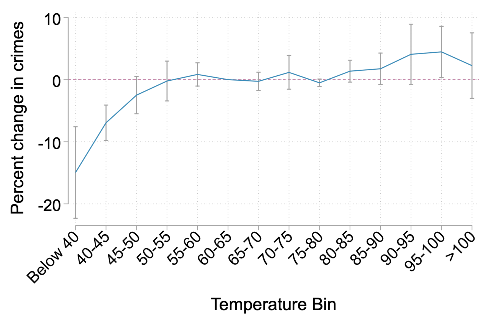
(b) Burglary



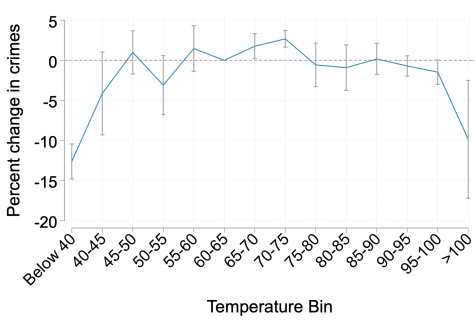
(c) Stolen property



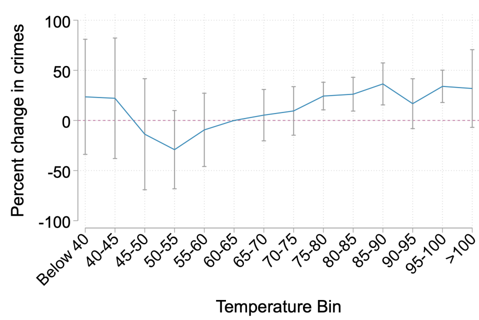
(d) Traffic



(e) Marijuana possession



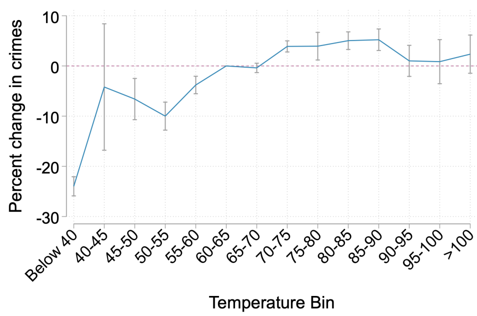
(f) Marijuana dealing



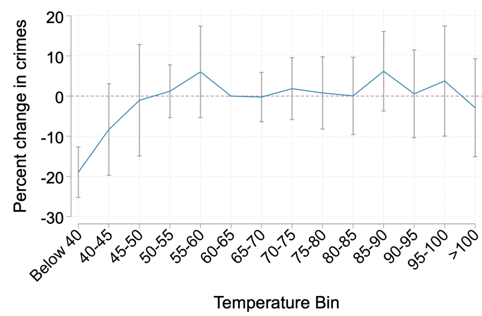
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control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

Figure 10: Heat's impact on arrests for other crimes

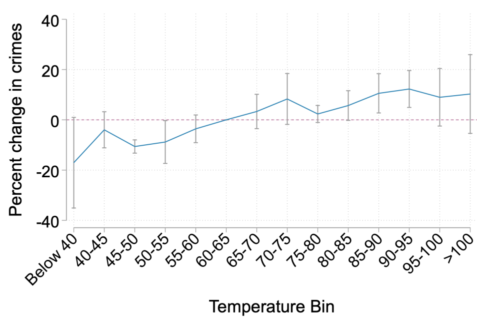
(a) Resisting police



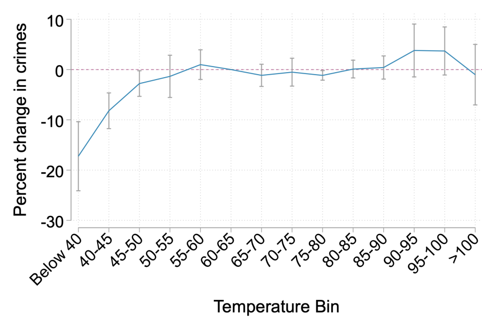
(b) Rioting



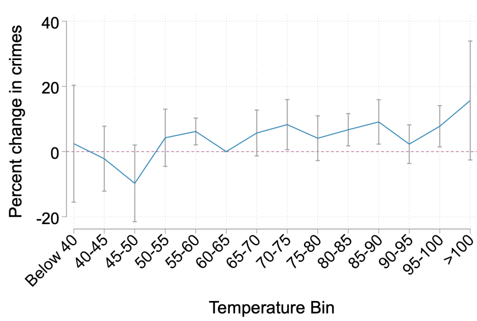
(c) Privacy violations



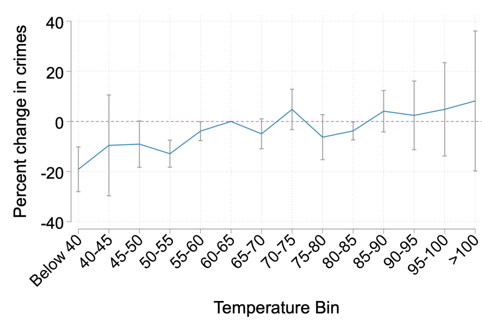
(d) DUI



(e) Hit & run

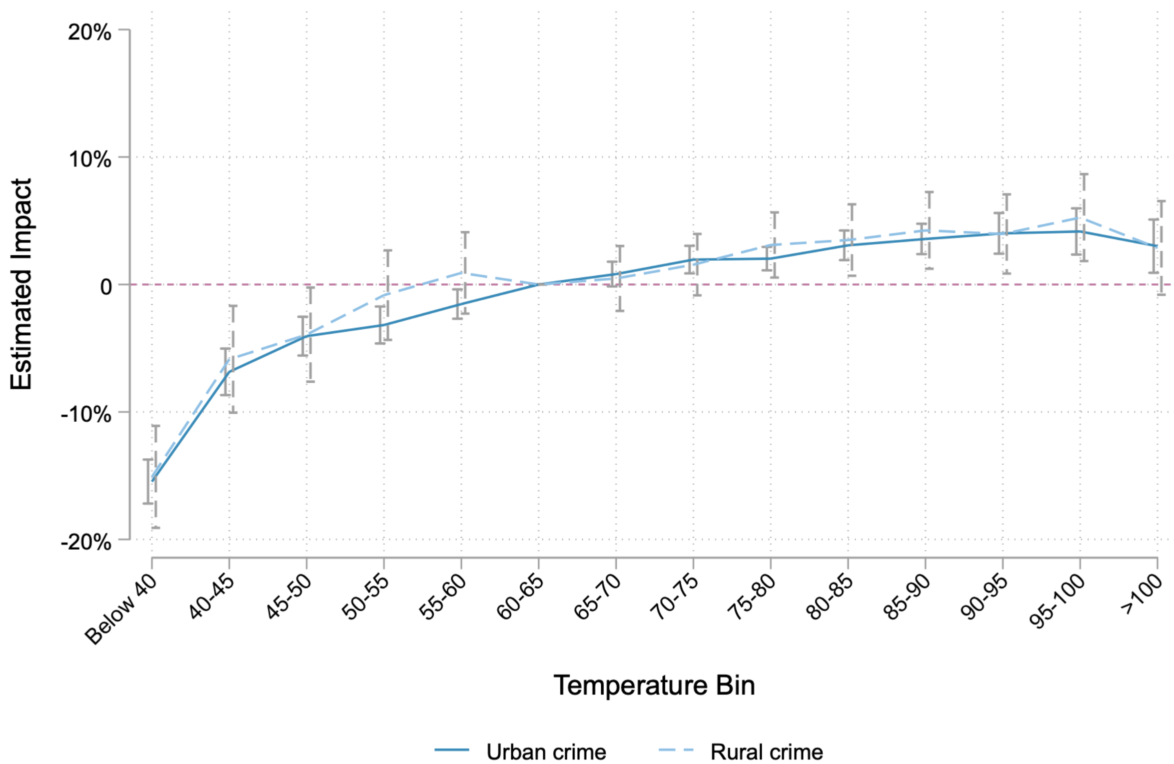


(f) Robbery



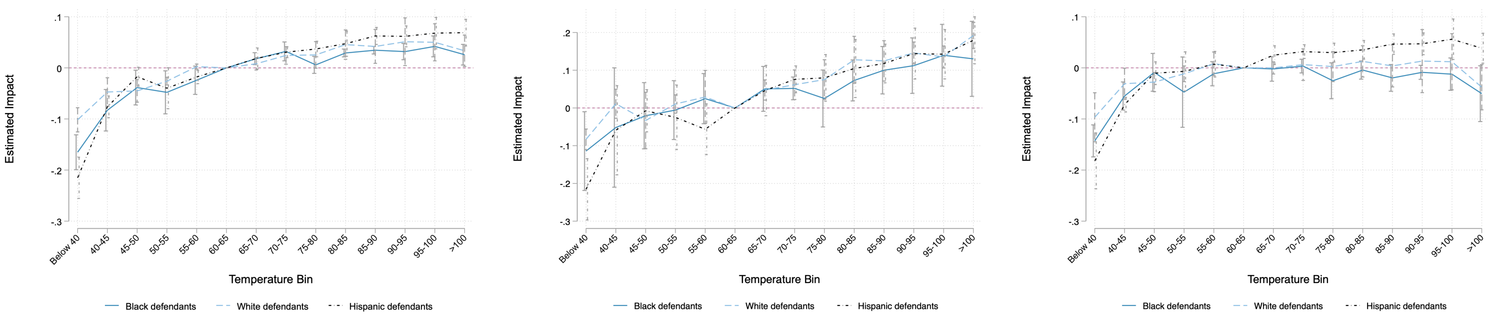
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control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

Figure 11: 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.

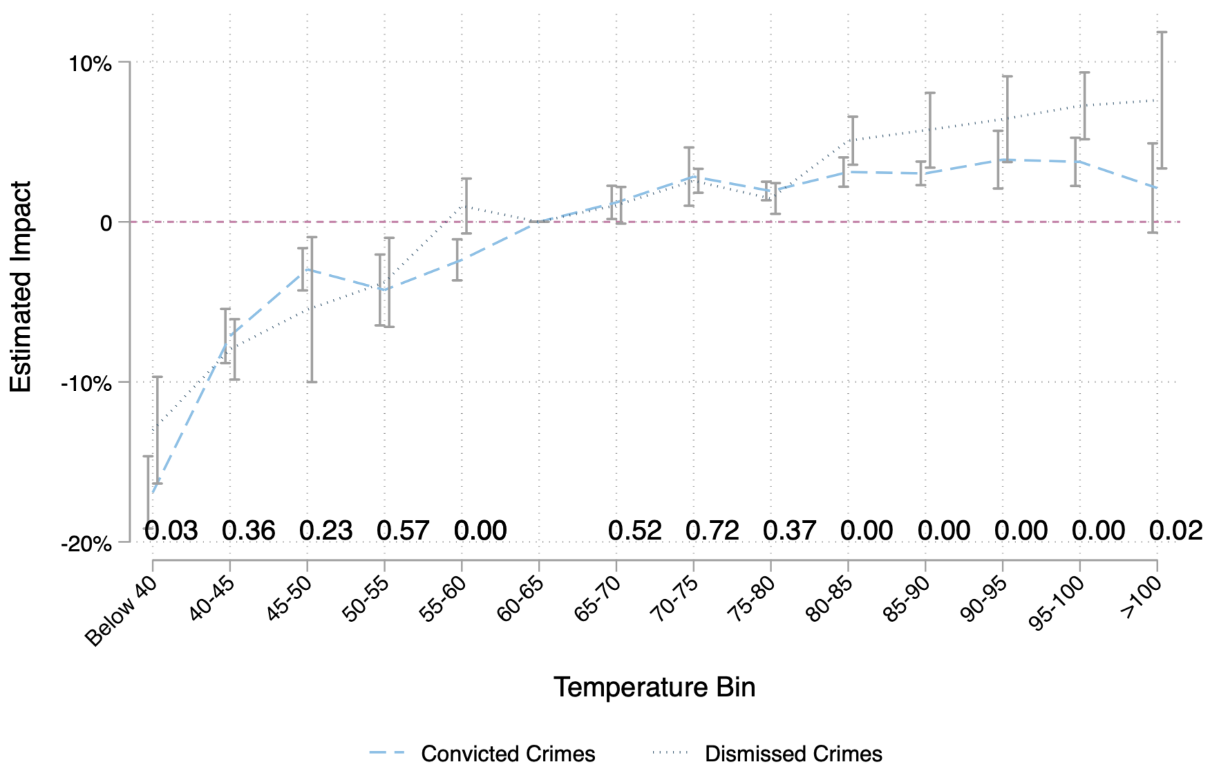
Figure 12: Heat's impact on arrests by race and ethnicity



All crimes | Violent crimes | Non-violent crimes

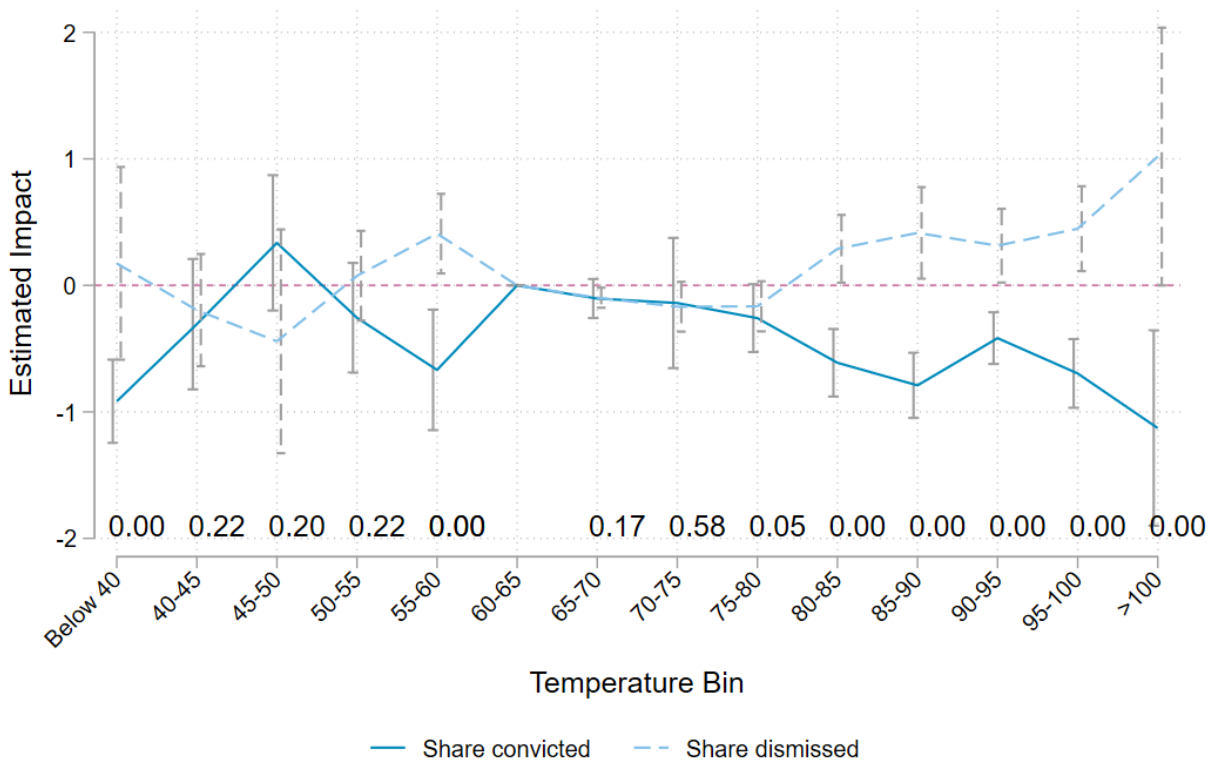
Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of arrests at the county-day level in each category. Y-axis shows the percentage decrease or increase in arrests relative to a $60-65°F$ day. Model includes county, year, month, and day of week fixed effects. We control 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 13: Change in dismissals and convictions



Notes: Estimated with a Poisson fixed-effects specification. Outcome is the count of cases that result in a dismissal or a conviction and cases are assigned to temperature bins based on the temperature on the day the arrest occurred. 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. P-values of the difference in coefficient estimates are at the bottom of the chart. Spikes indicate 95% confidence intervals.

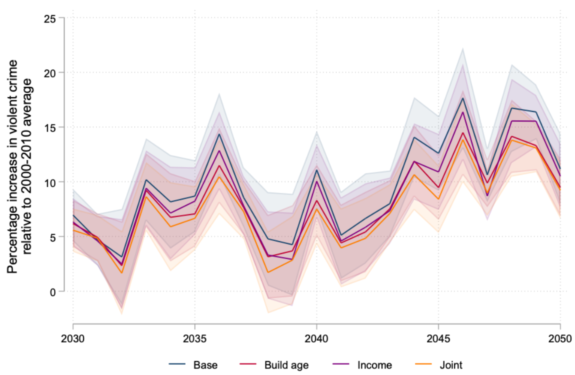
Figure 14: Impact of heat on the share of convictions and dismissals



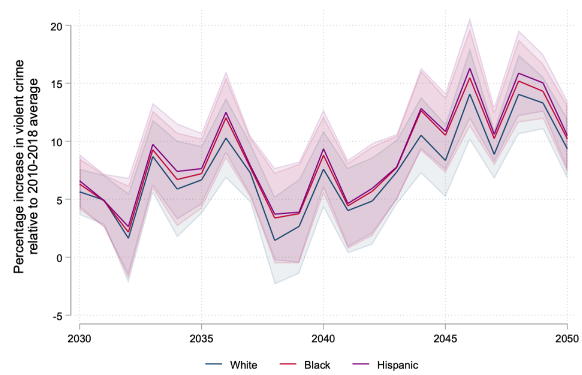
Notes: Estimated with a linear fixed effects specification. Outcomes are the share of arrests at the county-day level resulting in a conviction or dismissal. Estimates should be interpreted as the percentage point change in the share of arrests resulting in each outcome. For example, an arrest on a day above 100°F increases dismissal probability by 1pp. 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. P-values of the difference in coefficient estimates are at the bottom of the chart. Spikes indicate 95% confidence intervals.

Figure 15: Future impacts and adaptation

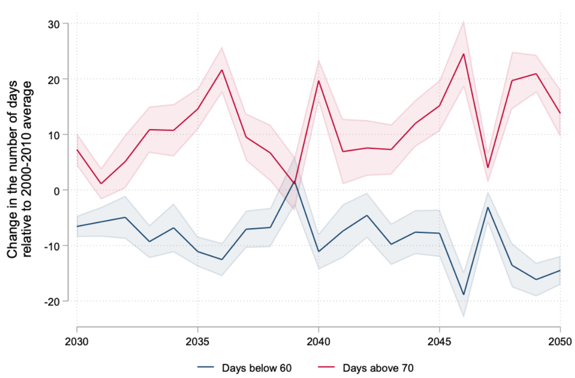
(A) Impacts by adaptation measure



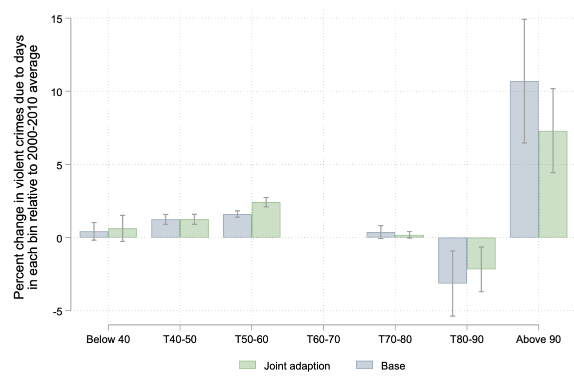
(B) Adaptation inclusive impacts by race



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

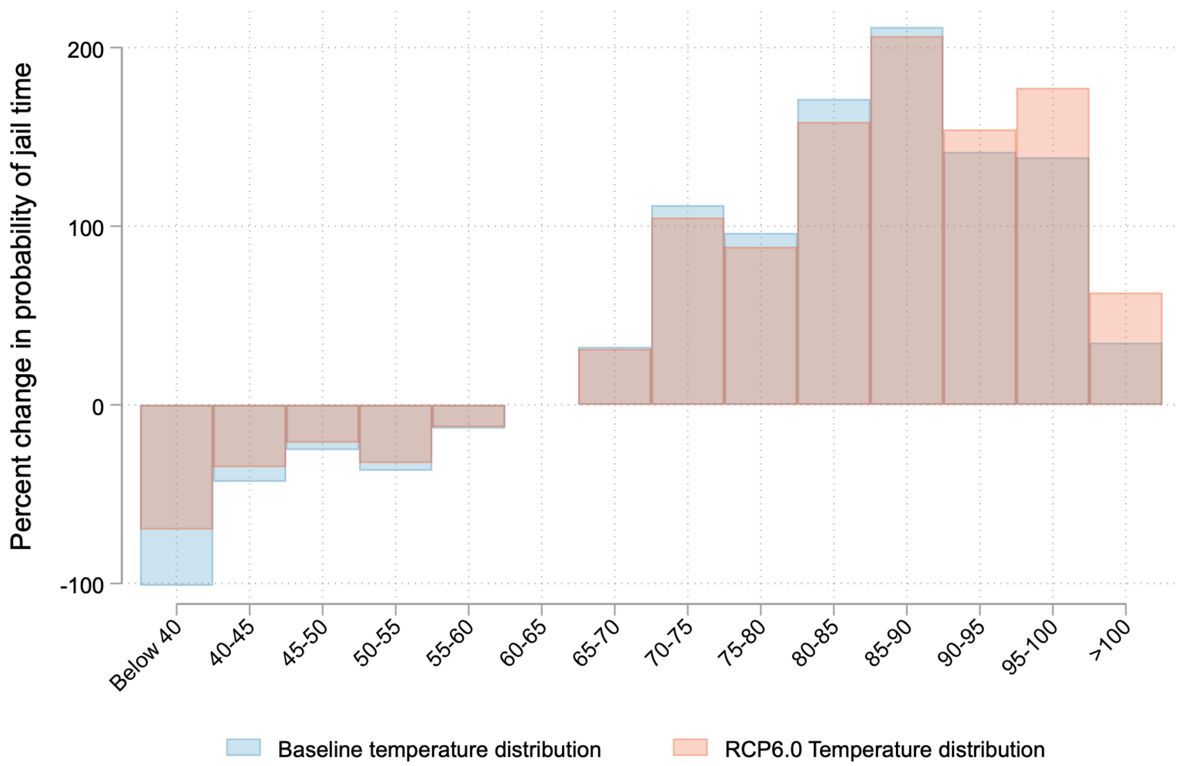


(D) Future impact by temperature bin 2050



Notes: 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 A5 and A6. For results under our aggressive adaptation scenario, see Figure A7. 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 A4. 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 60F, 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.

Figure 16: Change in the probability of arrest and conviction



Notes: We calculate the total percentage change, relative to a 65°F day, in the probability that an individual is arrested and convicted of a crime conditional on two temperature distributions. The first is the observed distribution in Texas in our sample. The second is the expected distribution of days in Texas in the RCP6.0 scenario. The change in probability for a given bin indicates that, for example, if all days above 100°F were replaced by 65°F days, the unconditional probability that an individual would be arrested and convicted of a crime would fall by approximately 25% relative to the probability in today's world. Put another way, given the current number of days above 100°F in a year in Texas, the unconditional probability that one will be convicted of a crime is 25% higher than if those days were all in the 65°F bin. Relative to the baseline temperature distribution, the RCP6.0 temperature distribution shows a 12% higher probability of arrest and conviction, assuming today's levels of adaptation to heat persist.

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Appendix 1 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. (2017). 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 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 (e.g. 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 (e.g. 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:

$$Impact_{byms} = \sum_{k=1}^{7} \text{Marginal Impact}_{iak} \times \left(Days_{cymsk} - \overline{Days_{cmsk,2000-2010}} \right) \tag{5}$$

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 2 Calculation of changes in probability of arrest and conviction

To calculate the change in the probability of arrest for the average Texan, we take our estimates of the marginal change in arrests for each temperature bin from our primary specification. For example, relative to a 65°F day, a day above 100°F increases the unconditional probability that an individual will be arrested for a crime by about 5%. Our data tell us that, at baseline, roughly 72% of those arrested on 65°F days are convicted. We use our estimates from the impact of heat on the probability of dismissal or conviction based on the temperature on the day of arrest and modify the probability of conviction in each temperature bin. For example, someone arrested on a day above 100°F is convicted roughly 70% of the time.

For each bin, we then multiply the probabilities of arrest and conviction and divide by the probabilities in the baseline bin. This gives us the percent change in the probability of conviction relative to the baseline temperature bin. Finally, we multiply these percent changes by the total number of days in each bin to see how much heat increases the probability of arrest and conviction in today's world relative to a world in which every day is 65-70°F. For comparison, we do the same exercise using the average across all of our projection models of the number of days in each temperature bin across Texas in 2050, predicted under the RCP6.0 scenario.

Appendix 3 Additional Tables

Table A1: Impact of heat on total crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T above 100F	0.047***	0.045***	0.044***	0.031***	0.028***	0.043***	0.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 95-100F	0.056***	0.054***	0.051***	0.046***	0.045***	0.053***	0.049***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 90-95F	0.048***	0.048***	0.043***	0.048***	0.049***	0.047***	0.044***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 85-90F	0.045***	0.045***	0.039***	0.042***	0.043***	0.044***	0.042***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
T 80-85F	0.042***	0.043***	0.039***	0.039***	0.040***	0.041***	0.040***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
T 75-80F	0.019***	0.023***	0.021***	0.019***	0.023***	0.022***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
T 70-75F	0.025***	0.030***	0.030***	0.025***	0.030***	0.030***	0.029***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
T 65-70F	0.018***	0.015***	0.013*	0.018***	0.015***	0.014***	0.014**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 55-60F	-0.003	-0.009*	-0.003	-0.002	-0.008*	-0.008*	-0.008
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
T 50-55F	-0.043***	-0.036***	-0.020***	-0.044***	-0.037***	-0.036***	-0.035***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 45-50F	-0.047***	-0.036***	-0.016***	-0.048***	-0.036***	-0.037***	-0.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T 40-45F	-0.073***	-0.066***	-0.048***	-0.075***	-0.066***	-0.065***	-0.064***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
T below 40F	-0.136***	-0.148***	-0.137***	-0.138***	-0.149***	-0.147***	-0.145***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	742,188	742,188	742,188	742,188	742,188	741,934	741,934
Fixed Effects:							
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes			Yes	Yes
Year	Yes	Yes	Yes			Yes	Yes
DOW		Yes	Yes		Yes	Yes	Yes
DOY			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. 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. *p=0.1, **p=0.05,***p=0.01.

Table A2: 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. *p=0.1, **p=0.05,***p=0.01.

Table A3: 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. *p=0.1, **p=0.05,***p=0.01. Compiled 14 Jul 2021.

Table A4: 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. The first quartile includes block groups with the least AC. *p=0.1, **p=0.05,***p=0.01.

Table A5: 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. *p=0.1, **p=0.05,***p=0.01.

Table A6: 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. *p=0.1, **p=0.05,***p=0.01.

Table A7: 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. *p=0.1, **p=0.05,***p=0.01.

TABLE A8: 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. *p=0.1, **p=0.05,***p=0.01.

Table A9: 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 A10: Impact of heat on the share of dismissals and convictions by race

	White		Black		Hispanic	
	Dismissed	Convicted	Dismissed	Convicted	Dismissed	Convicted
T above 100F	2.788***	0.452	-0.265	-1.702***	-1.104**	-0.781
	(0.860)	(0.325)	(0.358)	(0.305)	(0.545)	(0.640)
T 95-100F	0.976**	-0.443**	0.805***	-1.078***	-0.352	-0.813**
	(0.480)	(0.213)	(0.240)	(0.286)	(0.519)	(0.332)
T 90-95F	0.595	-0.130	0.396	-0.272	-0.564	-0.477
	(0.391)	(0.458)	(0.397)	(0.377)	(0.556)	(0.325)
T 85-90F	0.894***	-0.268	0.576*	-1.026***	-0.631**	-0.725**
	(0.305)	(0.190)	(0.323)	(0.181)	(0.247)	(0.320)
T 80-85F	0.438*	-0.323	0.674**	-0.632*	-0.384**	-0.801***
	(0.239)	(0.214)	(0.334)	(0.349)	(0.174)	(0.229)
N	1,040,623	545,640	791,782	1,040,623	545,640	791,782
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: Errors are clustered at counties and reported in parentheses. Regressions are weighted by the population of each race in each county-year. We control for the gender, race, and ethnicity of the defendant as appropriate. White defendants are white, non-Hispanic. All regressions are linear fixed effects. Coefficients indicate the percentage point change in the share of cases resulting in each outcome. *p=0.1, **p=0.05,***p=0.01.

Table A11: Rate of conviction and dismissal by crime type

	All crimes	Violent Crimes	Non-violent crimes
Dismissal rate	27.94	33.09	26.80
Conviction rate	49.32	31.63	58.12

Notes: Rates are calculated at the daily level and are reported as the percent of cases of each type that result in a given outcome on that day.

Table A12: Impact of prosecution action day heat on early release by race

	Dropped			Released		
	White	Black	Hispanic	White	Black	Hispanic
T above 90F	0.602	1.569	0.920	0.008	-0.007	-0.001
	(1.239)	(1.314)	(1.806)	(0.016)	(0.007)	(0.003)
T 85-90F	-0.961	-0.448	0.400	-0.003	-0.006	0.000
	(0.969)	(1.288)	(1.588)	(0.009)	(0.005)	(0.003)
T 80-85F	-1.606*	-0.974	0.175	-0.007	-0.006	-0.001
	(0.842)	(0.957)	(1.196)	(0.007)	(0.005)	(0.003)
N	842,953	387,392	749,037	842,953	387,392	749,037
Outcome mean:	35.95	32.24	37.36	0.01	0.01	0.01
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: Errors are clustered at the prosecutor level. Outcome is specified in column heading. All regressions are linear probability panel fixed effects. All regressions include control for dew point and minimum vapor pressure deficit.

Table A13: Impact of prosecutor action day heat on additional charges by race

	Added charges			Number of added charges		
	White	Black	Hispanic	White	Black	Hispanic
T above 90F	-0.047	0.776***	0.172	0.140***	-0.118*	0.377**
	(0.212)	(0.253)	(0.341)	(0.037)	(0.065)	(0.187)
T 85-90F	-0.504***	0.615***	-0.034	0.002	-0.094***	0.325**
	(0.181)	(0.183)	(0.241)	(0.030)	(0.030)	(0.147)
T 80-85F	-0.371***	0.075	-0.082	-0.067**	-0.148***	0.092
	(0.120)	(0.139)	(0.183)	(0.033)	(0.031)	(0.062)
N	842,953	387,392	749,037	21,682	9,735	19,485
Outcome mean, T60-65:	2.59	2.52	2.61	1.42	1.42	1.45
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: Errors are clustered at the prosecutor level. Outcome is specified in column heading. All regressions are linear probability panel fixed effects. All regressions include control for dew point and minimum vapor pressure deficit.

Table A14: Impact of court action day heat on trial outcomes by race

	Convictions			Dismissals		
	White	Black	Hispanic	White	Black	Hispanic
T above 90F	0.098	0.726	1.065*	-0.372	-2.144*	-1.463**
	(0.584)	(1.042)	(0.562)	(0.847)	(1.207)	(0.718)
T 85-90F	-0.295	-0.538	0.253	0.258	-0.083	-0.168
	(0.354)	(0.481)	(0.361)	(0.428)	(0.557)	(0.422)
T 80-85F	-0.054	-0.524	0.288	0.138	0.130	0.156
	(0.284)	(0.444)	(0.285)	(0.365)	(0.520)	(0.369)
N	496,734	276,274	354,219	496,734	276,274	354,219
Outcome mean:	63.76	66.49	64.57	30.24	26.83	29.86
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: Errors are clustered at courts. Outcome is specified in column heading. All regressions are linear probability panel fixed effects. All include controls for dew point as well as controls for race, gender, and ethnicity, as appropriate. White means non-Hispanic white.

Table A15: Impact of court decision day heat on court penalties by race

	Confinement			Fines		
	White	Black	Hispanic	White	Black	Hispanic
T above 90F	0.095**	0.010	0.062	0.040	0.043	0.024
	(0.045)	(0.060)	(0.051)	(0.028)	(0.032)	(0.022)
T 85-90F	-0.004	0.009	0.043	0.001	-0.034**	-0.009
	(0.027)	(0.035)	(0.027)	(0.017)	(0.017)	(0.014)
T 80-85F	0.021	0.037	0.024	-0.000	-0.016	-0.006
	(0.023)	(0.030)	(0.026)	(0.015)	(0.016)	(0.013)
N	338,795	161,721	259,818	470,439	248,610	343,346
Outcome mean, T60-65:	4.51	4.41	4.54	6.24	5.96	6.24
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: Errors clustered at courts. Outcome is specified in column heading. All regressions are linear probability panel fixed effects. All include controls for dew point as well as controls for race, gender and ethnicity, as appropriate. White means non-Hispanic white. All regressions include controls for the total cases heard in the day, dew point, and vapor pressure deficit minimum.

Table A16: 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. *p=0.1, **p=0.05,***p=0.01.

Table A17: 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												
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.

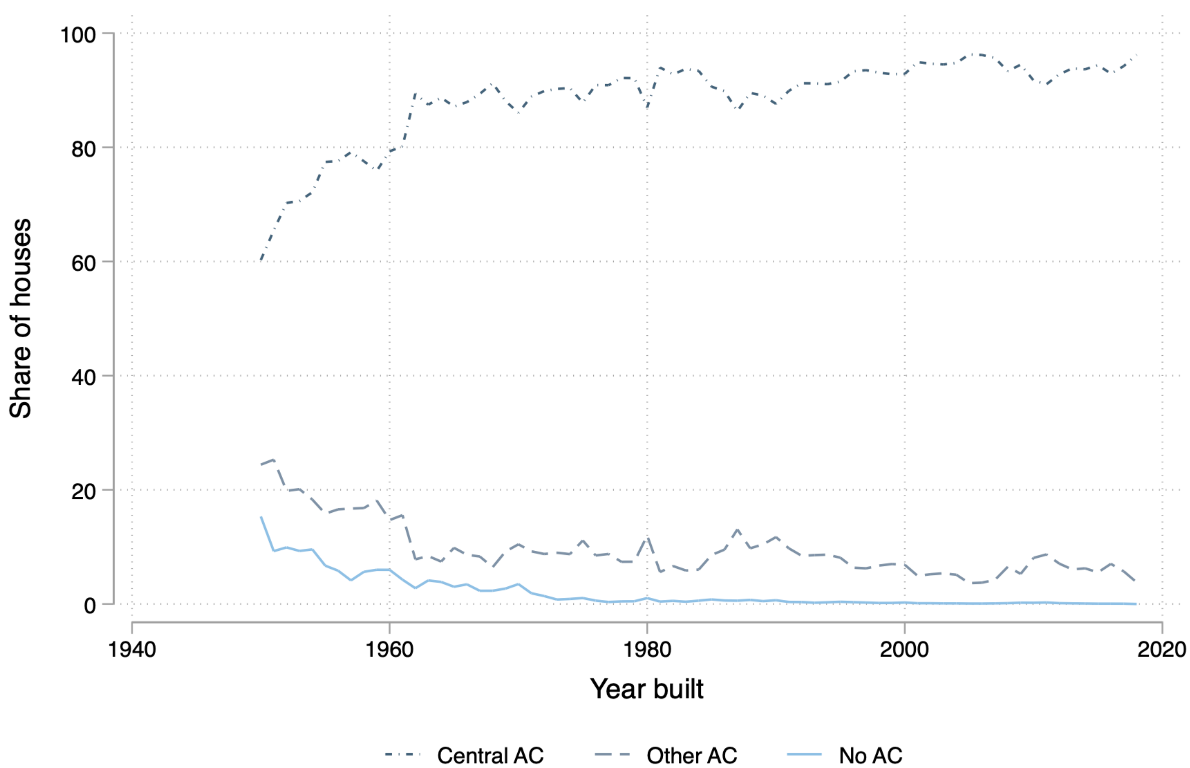
Table A18: 2050 quantile summary statistics

	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.

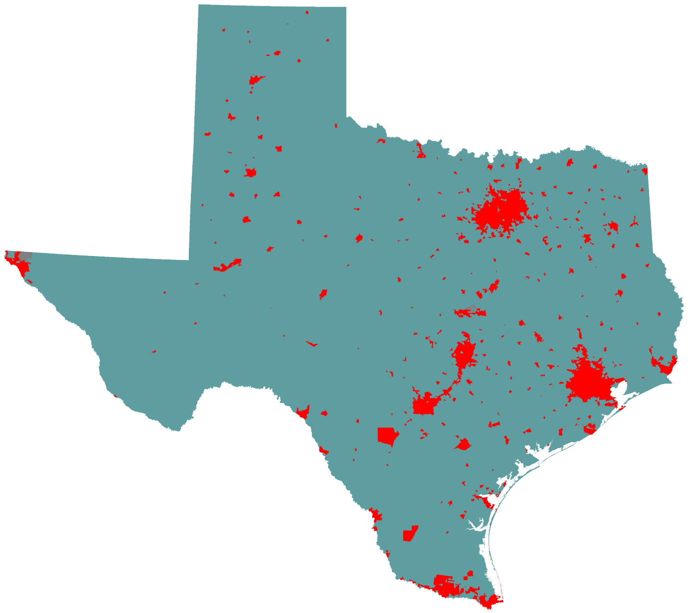
Appendix 4 Appendix Figures

Figure A1: Air conditioning penetration

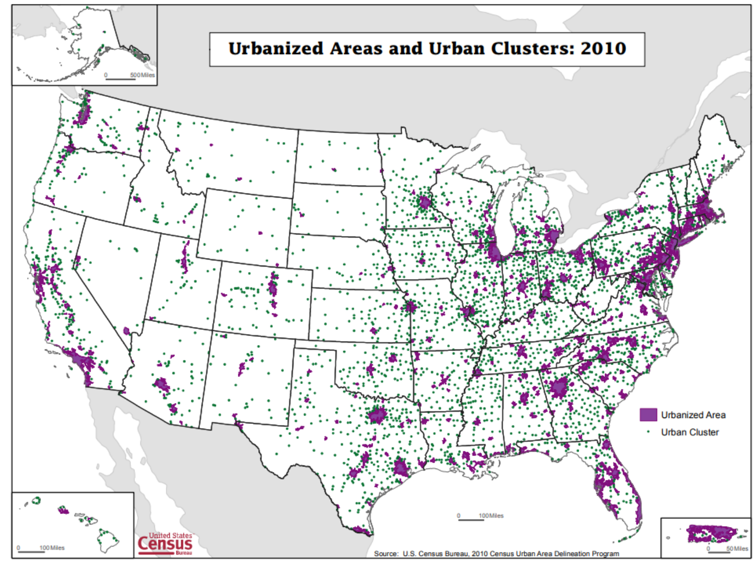


Notes: Categories are mutually exclusive - houses with other air conditioning do not have central air conditioning and vice versa. Data come from tax assessment records collected by CoreLogic. We bin houses built prior to 1950 into 1950. Only 10% of the houses in the CoreLogic Texas data are built before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

Figure A2: Urban block groups

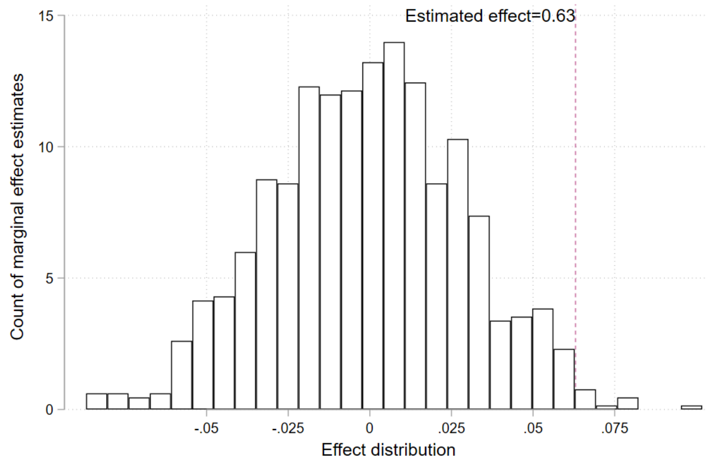


Notes: Red areas indicate block groups we consider urban. We categorize a block group as urban if 80% or more of the population is considered urban according to Census ACS data.

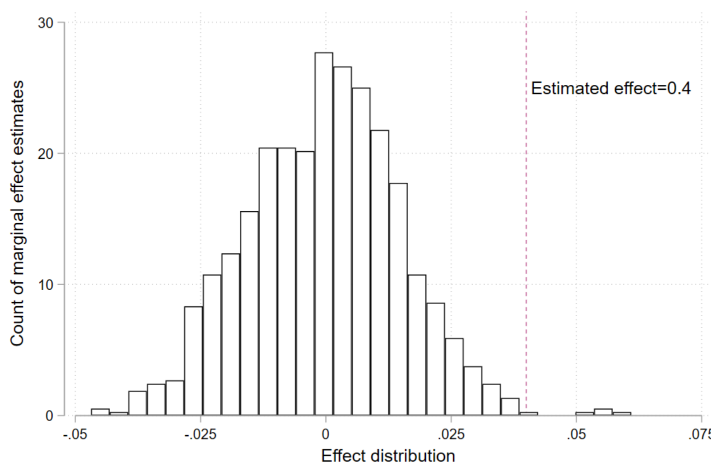


Notes: Map of areas the U.S. Census considered urban or an urban cluster in 2010.

Figure A3: Randomization inference tests



Outcome: length of confinement

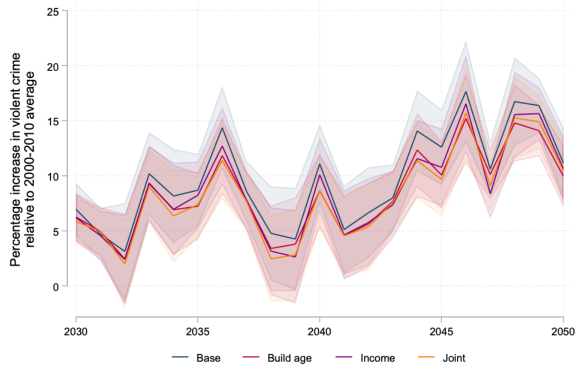


Outcome: amount of court fines

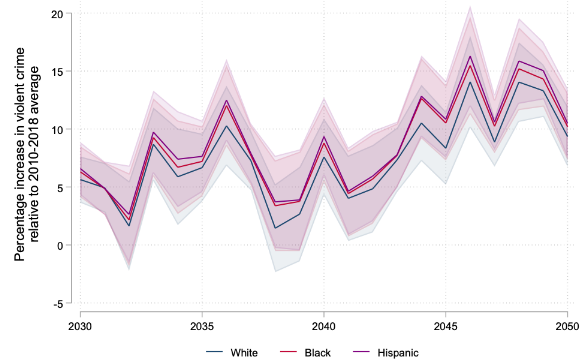
Notes: We re-estimate the impact of heat on the day of a judge's decision on each outcome 1,000 times, re-assigning temperatures randomly across days but preserving the overall distribution of temperature days. This generates a distribution of estimated effects centered on a null effect of zero. We observe that our true estimated effect is well outside this distribution, suggesting that it is not the result of random chance in the cases that happened to be decided on particularly hot days.

Figure A4: Future impacts and uniform adaptation, RCP6.0

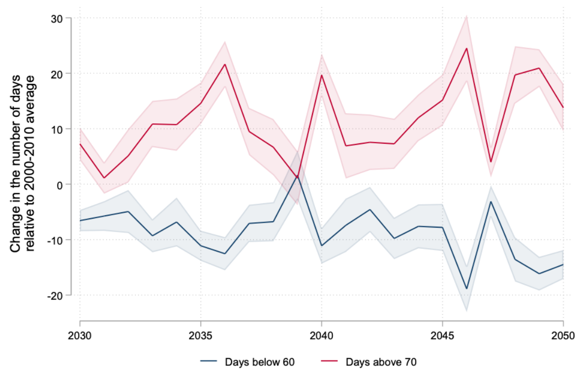
(a) Impacts by adaptation measure



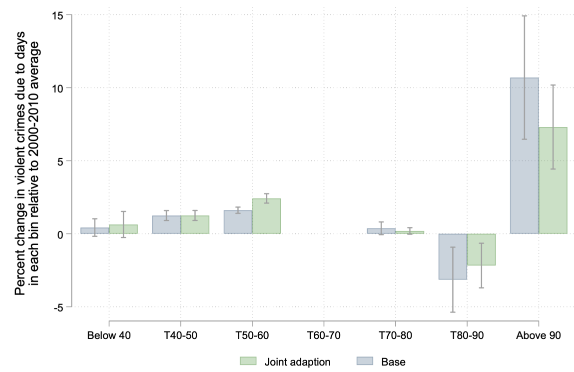
(b) Adaptation inclusive impacts by race



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



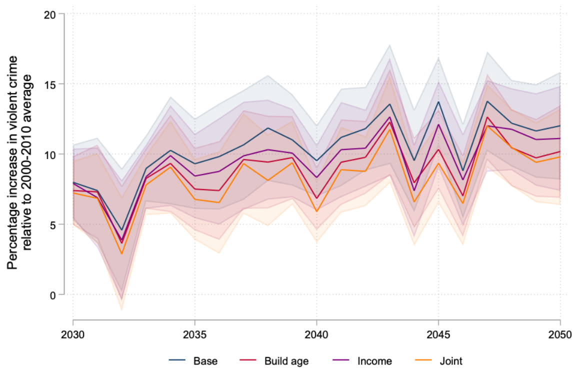
(d) Future impact by temperature bin 2050



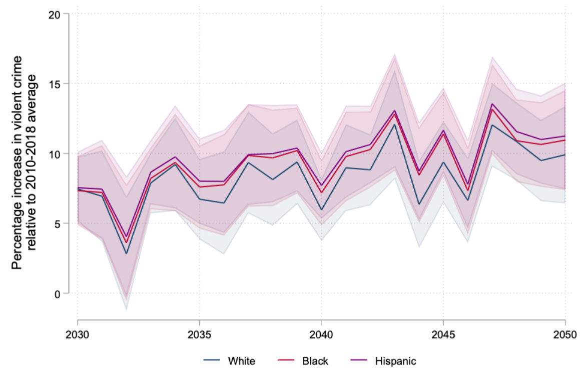
Notes: In all panels we show results using projections under the RCP6.0 scenario. We grow incomes and housing stock age according to the U.S. average from 2002 to 2019 and the average over the Texas sample, respectively. In Panel **A**, we show the average percentage increase in violent crime across 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 60F, 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 A5: Future impacts and adaptation, RCP2.6

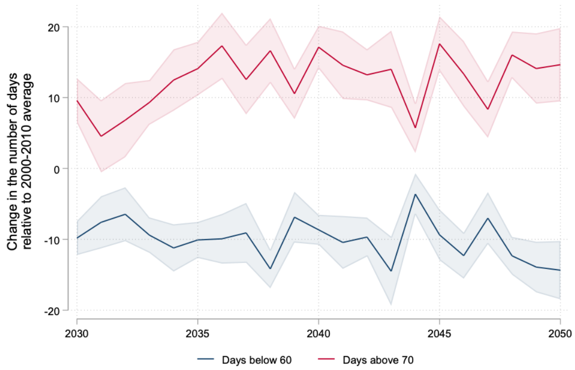
(a) Impacts by adaptation measure



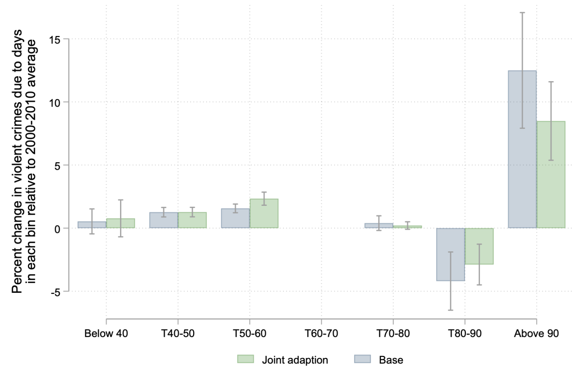
(b) Adaptation inclusive impacts by race



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



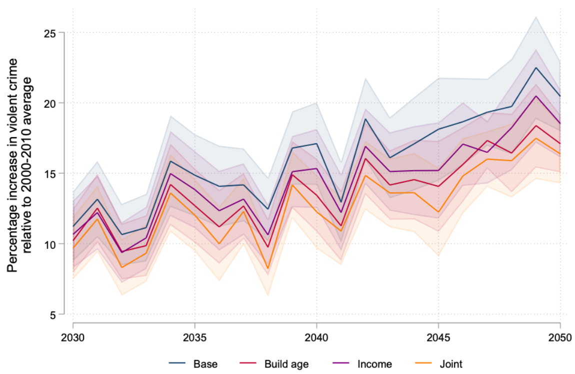
(d) Future impact by temperature bin 2050



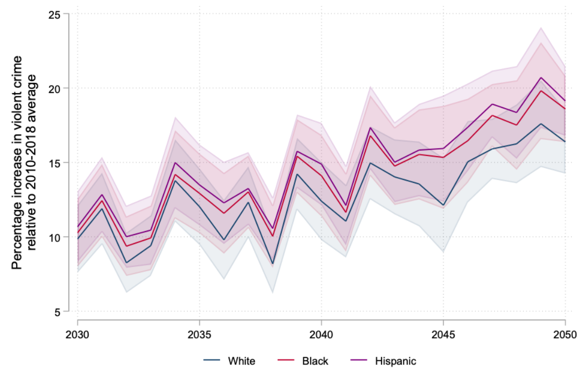
Notes: In all panels we show results using projections under the RCP2.6 scenario. In Panel **A**, we show the average percentage increase in violent crime across all of Texas due to the increase in average temperatures under four scenarios: using our pooled marginal estimates, using estimates that account 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 60F, 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 A6: Future impacts and adaptation, RCP8.5

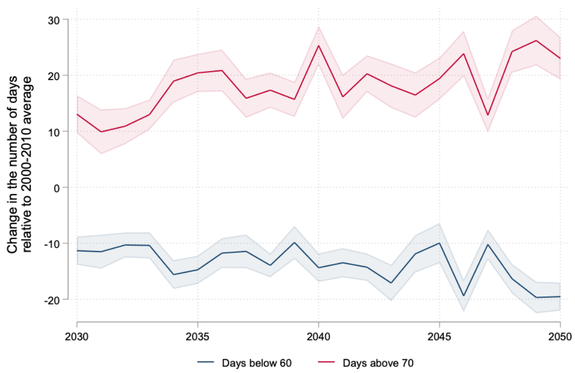
(a) Impacts by adaptation measure



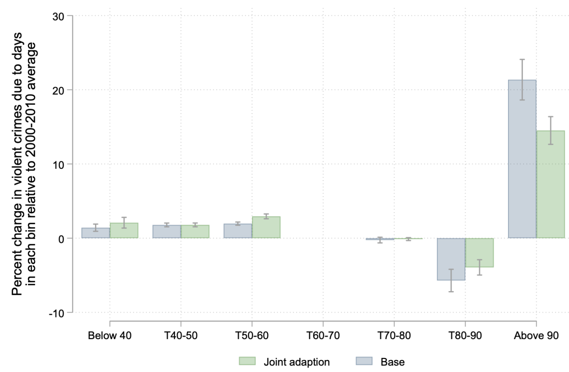
(b) Adaptation inclusive impacts by race



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



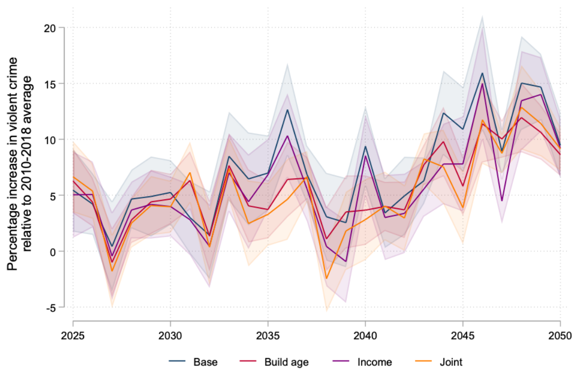
(d) Future impact by temperature bin 2050



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 60F, 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.

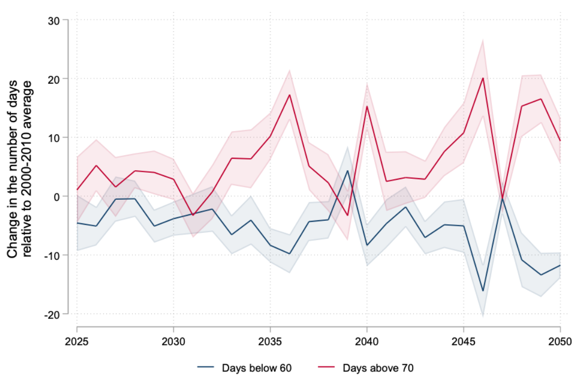
Figure A7: Future impacts and adaptation under aggressive adaptation

(a) Impacts by adaptation measure

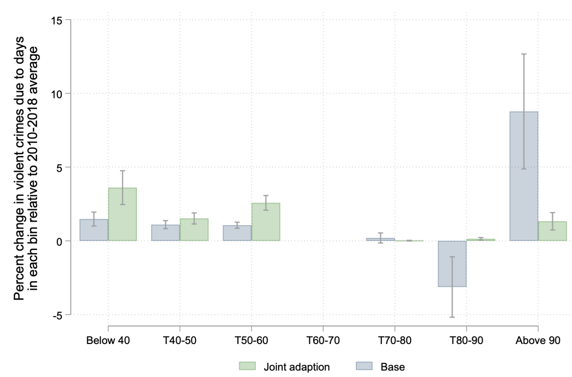


(b) Adaptation inclusive impacts by race

(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 60F, 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.