NBER WORKING PAPER SERIES

THE CAUSAL EFFECT OF HEAT ON VIOLENCE: SOCIAL IMPLICATIONS OF UNMITIGATED HEAT AMONG THE INCARCERATED

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Working Paper 28987
http://www.nber.org/papers/w28987

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2021

We are grateful to Alan Barreca, Teevrat Garg, Joshua Goodman, Benjamin Hansen, Kosali Simon, Justin Sydnor, and seminar participants at the 2021 AEA Annual Meeting, especially our discussant Jillian Carr and session chair Janet Currie; the 2021 Association of Environmental and Resource Economists meeting; the 2019 Heartland Environmental and Resource Economics Workshop; and the University of Wisconsin-Madison Health Economics Working Group. We gratefully acknowledge Audrey MacAfee and Lynn Mullen at the Mississippi Department of Corrections for providing raw extracts of inmate data, and Zihan Hu and Youngjae Hwang for excellent research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 28987
July 2021
JEL No. I1,K38,Q54

ABSTRACT

Correctional facilities commonly lack climate control, producing a setting absent endogenous responses to hot weather like avoidance, adjustment, and mitigation. We study daily weather variation across the state of Mississippi, and show that high temperatures increase intense violence among the incarcerated. Days with unsafe heat index levels shift both the intensive and extensive margins of violence, raising daily violent interactions by 20%, and the probability of any violence by 18%. Our setting cleanly identifies the effect of heat on violence, and highlights previously unobserved social costs of current facility infrastructure. Rising global temperatures could substantially increase violence absent adjustment.

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"I pray thee, good Mercutio, let's retire.
The day is hot; the Capulets, abroad;
And if we meet we shall not escape a brawl,
For now, these hot days, is the mad blood stirring"

(Romeo and Juliet[1])

1 Introduction

We address the causal relationship between heat and violence using daily data from correctional facilities in the state of Mississippi. We find that high ambient temperatures increase both the number of violent events and probability of any violence. The lack of temperature control in Mississippi facilities, plus a population that cannot relocate on hot days, illustrates policy implications regarding prison reform; incarcerated individuals are regularly subject to environments that raise direct health concerns and contribute to additional convictions and extended sentences via induced intra-facility criminal behavior. Our results avoid common confounders in the heat and violence literature with a unique situation where daily accommodations are not endogenous to heat. This setting causally links higher temperatures to more violence, enabling a more accurate understanding of the potential costs of rising global temperatures.

A combination of climate change and aging infrastructure means a prison population of over 2.2 million people in the United States (US) is exposed to rising temperatures with no opportunity for mitigation. Excessive heat in prisons drives a current constitutional battle regarding treatment of prisoners under the Eighth Amendment, which forbids cruel and unusual punishment (Blinder, 2016). Though judges have ruled in support of requiring temperature control for incarcerated individuals, many state regulations continue to exclude prisons from temperature control mandates. For example, a recent Texas law requires county jails to hold inmates in temperatures between 65 and 85 degrees Fahrenheit (F), but does not extend that requirement to the large state prisons.[2] While localities may cite cost issues in

[1]From *Romeo and Juliet*, by William Shakespeare, Act 3 Scene 1.
[2]The bill, H.B. No. 936, is here: https://capitol.texas.gov/tlodocs/86R/billtext/html/HB00936I.htm.

addressing temperature mitigation, some may withhold air conditioning (A/C) in prison as a policy tool to appear "tough on crime".[3] Yet, prior studies show broad public support for prison A/C in hot climates (Lenz, 2002). The lack of temperature control raises important social cost issues, as prisoners experience a disproportionate share of chronic illnesses that interact with heat, making temperature a problematic medical concern for this population (Skarha et al., 2020; Chammah, 2017; Bavafa and Mukherjee, 2019).

We find that very hot days result in more acts of prison violence, increasing both the number and probability of these acts.[4] Effects arise on days with average temperatures of 80F degrees or higher (80F+), all of which have maximum heat index levels considered unsafe at some point in the day, and some reaching over 120F. Intensely hot days increase daily prison violence by approximately 20%, or an average of 0.02 events, compared to a baseline rate of approximately 0.1. The probability of any violent act increases by 0.9 percentage points, an increase of approximately 18% on a baseline of five percentage points. These are severe violent events with substantial social costs, comprised of killing or physically assaulting another individual resulting in serious injury. The system typically processes these acts as new crimes, generating extended sentences for those instigating violence.

Violence in this context has a policy solution of mitigation in the form of A/C or more modern prison structures enabling temperature control. Reducing such violence would help correctional facilities serve their purpose of delivering court-assigned enforcement while avoiding additional incarceration costs. Based on our findings, unmitigated exposure to heat generates an additional 44 cases of intense violence per year in the Mississippi correctional system alone. Implications for prison policy extend beyond Mississippi, as according to data provided by the Prison Policy Initiative (PPI), as of 2019, 13 generally "hot" states do not have universal A/C in their systems: Alabama, Arizona, Florida, Georgia, Kansas, Ken-

[3]See "Texas spent $7 million to fight against A/C in a prison. It may only cost $4 million to install" (The Texas Tribune, Aug. 29, 2018, by Jolie McCullough). In Louisiana, lawmakers spent over $1 million fighting the implementation of A/C systems that cost $225,000 (The Press Herald, June 13, 2016, by Michael Kunzelman).

[4]To date, evidence on the impact of heat in prisons has been limited to monthly analyses and mortality (Haertzen et al., 1993; Motanya and Valera, 2016).

tucky, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Texas, and Virginia (Jones, 2019).

Our results contribute to the study of temperature and violent and destructive behavior in more general conditions, with a unique setup that largely avoids common confounders in the literature: avoidance behavior, mitigation, reporting bias, and income effects. By definition, prison limits both mitigation and avoidance behavior; prisoners cannot leave on hot days, and no correctional facility in our analysis provides any form of A/C to incarcerated individuals over the studied time period (Holt, 2015). And while evidence suggests that there is increased violence in police-civilian interactions on hot days (Annan-Phan and Ba, 2019), in studies of temperature and violence using traditional crime statistics, temperature itself can drive both criminal activity and observance of such activity. Heat can cause police to alter patrol behavior, and potential witnesses (and victims) may remain indoors (Carr and Doleac, 2018). Heilmann, Kahn and Tang (2021) use detailed police report data from the city of Los Angeles to show that police behavior changes for some crimes, and that the extent of change can vary by neighborhood income. Garg, McCord and Montfort (2020) find more direct income effects, showing conditional cash transfers in Mexico substantially reduce the relationship between temperature and homicide rates.

In our setting, correctional facility guards responsible for incident reports must be in the facility monitoring inmates regardless of temperature, and potential witnesses (other inmates) must also remain present.[5] Finally, our study design avoids interactions between temperature and income. Income is an important factor in the study of both conflict and climate, and separating the link between resources and violence is difficult when addressing questions of temperature. In our case, a lack of significant financial employment for the currently incarcerated means that resources offer limited explanation to the link between

[5]Temperature may still impact guard effort, with two caveats. First, guards have access to temperature-controlled break rooms, introducing a source of heat mitigation. Second, our focus on more severe violent acts reduces guard ability to dismiss and/or not report outcomes. Heat may also cause guards to instigate or escalate violent behavior. We cannot separately estimate the role of this channel, but the net effect remains the same for both estimation and policy purposes.

temperature and behavior. Jointly, these conditions mean that we can identify a relationship between heat and violence, which is relevant for other contexts with limited scope for mitigation and avoidance, such as in developing countries, lower-income areas, and regions without stable electricity grids.

Prior literature has found convincing correlations between temperature and crime, though the magnitude of effect is difficult to identify because of the aforementioned endogeneity in mitigation and avoidance. Several papers document a link between temperature and violent crime in the US (Ranson, 2014; Jacob, Lefgren and Moretti, 2007; Mares and Moffett, 2019). Colmer and Doleac (2021) use this correlation to show that states with lenient gun laws exhibit higher rates of gun violence in response to higher temperatures. In a laboratory setting, Almås et al. (2019) find that heat, or "thermal stress", increases one's willingness to destroy another person's assets. The evidence on temperature and crime is linked to the heat-aggression hypothesis, which, for example Larrick et al. (2011) show is evident in baseball players who exhibit more hostility in hot temperatures.[6]

As we show in Sections 2 and 3, our detailed data allow us to use daily variation from annual weather patterns to identify effects. After presenting our main results in Section 4, we demonstrate the robustness of our findings in Section 5. In Section 6, we show that heat effects appear unique to matters of intense violence, with no such effects for less harmful acts or other forms of facility misconduct, and that current temperatures play a larger role than cumulative effects. In Section 7, we use back of the envelope estimates to extend the impacts of heat in prison beyond our sample. We further discuss the policy implications of our results in Section 8.

2 Data

Inmate Violence and Population

We use incident-level inmate misconduct data from the Mississippi Department of Cor-

[6] Other environmental factors shown to be connected to crime include pollen (Chalfin, Danagoulian and Deza, 2019), daylight (Doleac and Sanders, 2015), and pollution (Herrnstadt et al., 2017).

rections (MDOC). The data span 1/1/2004 through 12/31/2010, and contain the universe of all infractions within the state correctional system. Infractions are standardized across locations within the MDOC system, and are described clearly in the state's Inmate Handbook.[7] Inmates have an incentive to avoid these infractions because they can result in reduced privileges, and parole boards view them unfavorably when deciding on early release. The MDOC explicitly states in the Handbook that "inmates who violate rules can receive disciplinary actions to include detention and loss of visitation, phone and canteen privileges, loss of Earned Time or custody reduction." The violent acts we study would also be processed as new crimes, resulting in separate court-assigned punishment. Guards are tasked with reporting all infractions as they occur.

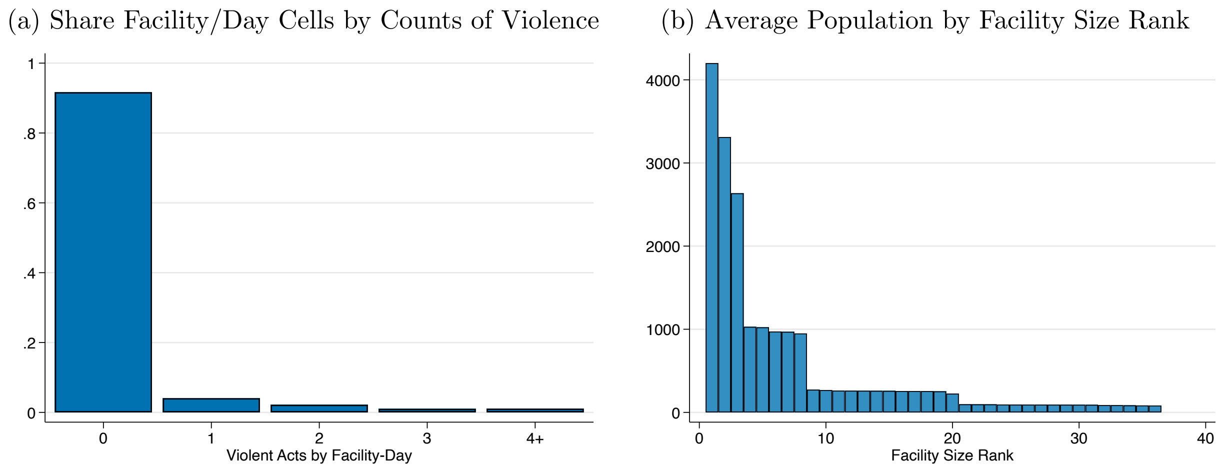
Our data includes 36 facilities located around the state, yielding substantial within-state geographic variation in temperature for any given day. There are eight large state prisons, which we later analyze separately, and a mix of regional prisons and jails. We group incidents into five broad categories: violence, aggressive behavior, disobedience, refusal to work, and riotous behavior. Appendix B provides the full list of incidents and their categorization. We focus on the violent incident category, including: "killing or assaulting anyone", "fighting (except for self-defense)", and "assaultive action against any person resulting in serious physical injury". For each incident, the data provide the date, facility, and detail for categorization. This combination of incident type and location is unique to the Mississippi prison data, critical to our study as we link the incident to daily temperature metrics while controlling for facility-specific fixed effects.

Our facilities average 65 intensely violent acts per year, though events are not uniformly distributed across days or facilities. Panel (a) of Figure 1 shows the histogram of counts of violent acts by facility/day cell. Panel (b) shows the histogram of average population by facility, ranked from largest to smallest.[8] Many facility/day cells have no violent acts, and

[7]Available here: https://www.mdoc.ms.gov/Inmate-Info/Pages/Rule-Violations.aspx

[8]Population data are at https://www.mdoc.ms.gov/Admin-Finance/Pages/Daily-Inmate-Population.aspx, last accessed May 4th, 2021. We limit analysis to facilities with both infraction and population data, the latter being the limiting factor. We repeated analysis including all facilities regardless of population data

Figure 1: Count of Facility-Day Observation by Indicated Range



Notes: Panel (a) plots the fraction of facility/day observations by their raw count of violent acts, where "4+" includes all observations with a value of four or larger; Panel (b) plots the daily average reported population for each facility, ordered from largest to smallest.

some facilities in our data have relatively small populations while others are large. The daily population minimum is 44, and the maximum is 5,706, and the average facility population across all 2004-2010 ranges from 81 to 4,309.

Temperature

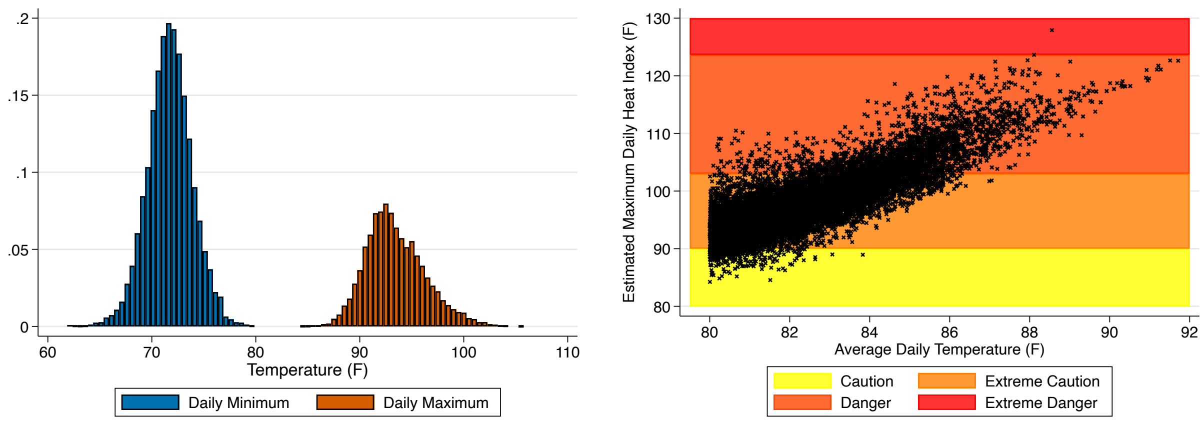
We combine incident data with daily information on temperature, assigning temperatures to facilities using the county in which they are located. Our 36 correctional facilities cover 29 counties — 22 counties have unique facility-to-county matches, and the remaining seven each have two facilities. We use the PRISM weather data, aggregating at the county/day level and including daily minimum and maximum, along with daily rainfall.[9] As PRISM weather data are partially imputed, we repeat analysis using Global Surface Summary of the Day data from the National Oceanic and Atmospheric Administration (NOAA). These data are at the weather station/day level, and also include minimum and maximum daily temperatures. We also provide estimates using specific location of the facility, based on the latitude and

with similar results.

[9] These data come from Schlenker and Roberts (2009), with updates for later years provided by Wolfram Schlenker.

Figure 2: Minimum and Maximum Temperatures and Maximum Heat Index for all Days with Average Temperature 80F+

(a) Distribution of Temperatures (F) (b) Estimated Heat Index (F)



Notes: Panel (a) shows the distribution of daily minimum and maximum temperatures for all days in our data with an average daily temperature of 80F+. Histograms show the frequency of daily minimum and maximum temperatures at the county level, conditional on the average temperature of the day being 80F+, where we calculate averages using $\frac{min+max}{2}$. Temperature data are from the PRISM data set: see Section 2 for details. Panel (b) shows the maximum heat index estimated for each day with an average daily temperature of 80F+. We describe estimation of the heat index in Appendix C. Data on humidity are from the NOAA quality controlled data sets (USCRN/USRCRN from Diamond et al. (2013)) for the two available stations in Mississippi. Shaded regions show the heat-index-related classifications of possible harm according to the NOAA.

longitude of its address, to assign facility-level temperature.[10] We use the average of the daily minimum and maximum as our measure of daily temperature. Appendix Figure A-1 shows that all three measures yield similar distributions of average daily temperature.

3 Methods

We first convert our continuous temperature data into bins, following the literature on the nonlinear effects of temperature on human health (Deschênes and Greenstone, 2011; Barreca et al., 2016; Heutel, Miller and Molitor, 2020). We construct seven bins by degrees in Fahrenheit: less than 30F, 30-39F, 40-49F, 50-59F, 60-69F, 70-79F, and 80F and above (80F+). About 62 days in a year (17%) fall in the 80F+ range. Panel (a) in Figure 2 shows the distribution of maximum and minimum temperatures for days averaging 80F+, which

[10]We create a temperature estimate using all stations within 50 miles of the county centroid or facility address, weighted by $1/distance$.

can get very hot during the day, with an average maximum temperature of 93F. Standard temperature measurements fail to account for humidity, which can increase the stress effects of heat. The heat index, or "feels like" temperature, captures how temperatures feel in the presence of humidity, which is high in Mississippi.[11] The heat index is classified in four levels related to the danger of heat stroke, heat exhaustion, and heat cramps: caution (80-90F), extreme caution (90-103F), danger (103-124F), and extreme danger (125F or above).[12] For days averaging 80F+, many observations involve time in the most dangerous categories, with potentially even higher temperatures indoors.[13]

Appendix Table A-1 shows means and standard deviations for the share of days by temperature bins, as well as the number of violent acts per day and the probability of any violent act. Across our 36 facilities and seven years of data, we have 92,052 facility-day observations. The average number of violent acts per day is 0.096, with a standard deviation of 0.564. The average probability of a violent act is 0.050, with a standard deviation of 0.217. The average share of days in the 80F+ range is approximately 17%, though this varies substantially by geography. Figure 3 shows counties containing correctional facilities in our data, split into quintiles by share of days with an average temperature of 80F+, ranging from approximately 9% to 25%. Markers show locations of facilities: circles indicate a single facility at that location, and diamonds indicate two locations sharing the same address (e.g., a main facility and a satellite facility on the same grounds).

Our semi-parametric model estimates:

$$y_{f,t} = \alpha_a + \theta_w + \omega_f + \lambda_f * t + \delta_1 rain_{c,t} + \delta_2 rainsq_{c,t} + \sum_{j=1}^{J} \beta_j^{TMEAN} TMEAN_{c,t} + \epsilon_{f,t}. \quad (1)$$

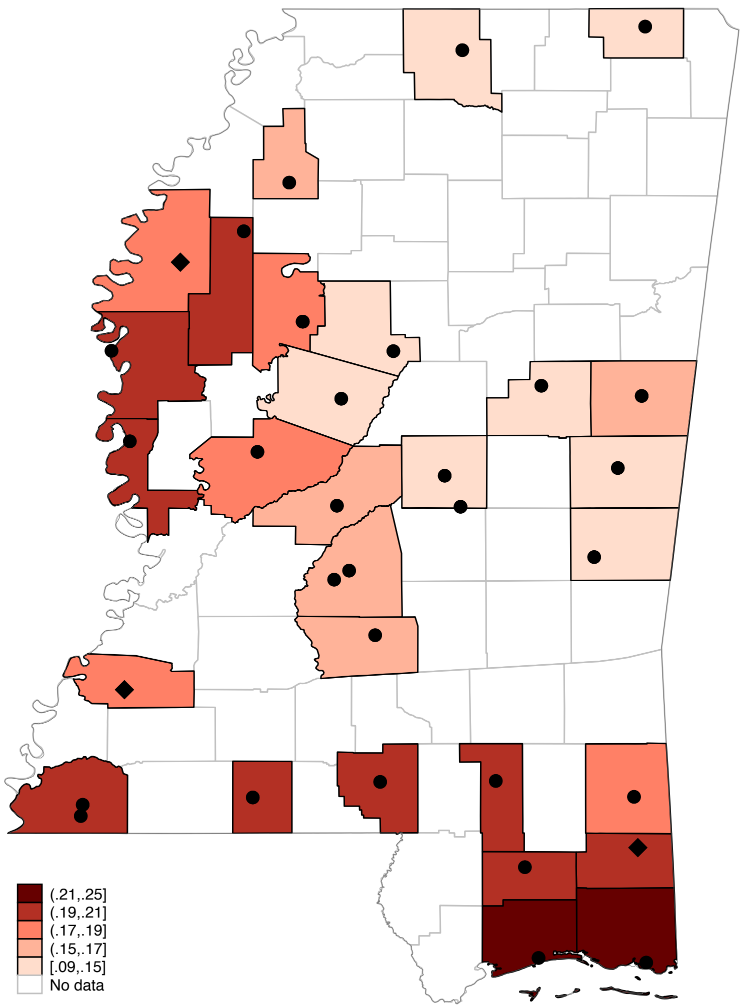
The dependent variable y is either (a) the number of violent acts in facility f on day t,

[11] See Appendix C for our method for calculating the heat index.

[12] The classifications are from: https://www.weather.gov/ama/heatindex

[13] Alexi Jones of the PPI notes, "Prisons are often built of heat-retaining materials which can increase internal prison temperatures [...] Because of this, temperatures inside prisons can often exceed outdoor temperatures"(Clarke, 2019). In Appendix E, we provide several examples of reports of extreme indoor heat in prisons and the potential associated health consequences.

Figure 3: Facility Locations and Share of 80F+ Days per Year



Notes: Temperature ranges split the 29 included counties into quintiles with an average share of days that are 80F+ per year. Counties without fill are not in our analysis. Markers show facility locations: circles indicate a single facility at that location, and diamonds indicate two locations sharing the same address (e.g., a main facility and a satellite facility on the same grounds).

or (b) a binary variable indicating any violent act in facility f on day t. Fixed effects capture effects for year (α_a), week of year (θ_w), facility (ω_f), and facility-specific linear time trends ($\lambda_f * t$). Facility fixed effects are important for many reasons, including the presence of private prisons which can impact prison conditions and thus the number of inmate infractions (Mukherjee, 2021). Year fixed effects adjust for common year shocks at the state level. Week of year effects adjust for common time-of-year effects across the state, such as the holiday season, which historically occurs during colder times of the year and has higher rates of facility violence.[14] Facility trends allow for potentially correlated relationships between growing/shrinking prison populations, temperature changes, and baseline violence across time. We denote variation of weather at the county level using c. The $rain$ control includes daily rainfall, in centimeters, in both linear and quadratic form in case rainfall correlates with temperature in a manner affecting behavior. We cluster standard errors at the facility by calendar month level, as variation in treatment occurs both spatially and over time. As very few counties have more than one facility, this is approximate to clustering by county by calendar month. In the Appendix, we explore alternate clustering choices, including Wild bootstrap to deal with limited clusters, with little effect on statistical significance.

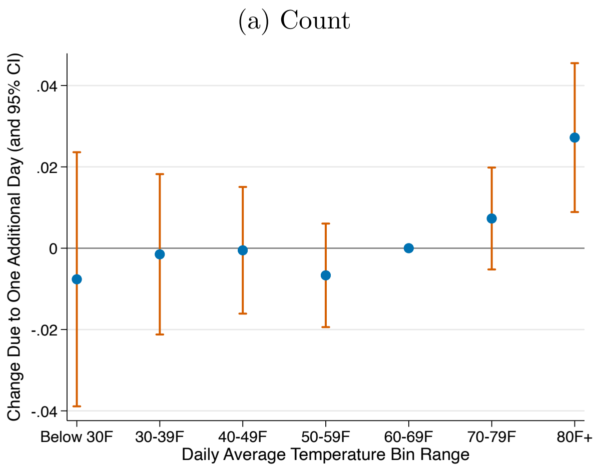
The main coefficients of interest are those contained within $TMEAN$. In our basic specification, this represents six temperature bins: Below 30F, 30-39F, 40-49F, 50-59F, 70-79F, and 80F+. The omitted bin (and reference category) is 60-69F, as evidence in economics literature on extreme temperatures and health, including Deschênes and Greenstone (2011), Barreca et al. (2016), and Heutel, Miller and Molitor (2020), shows that deviations from this range increase mortality.

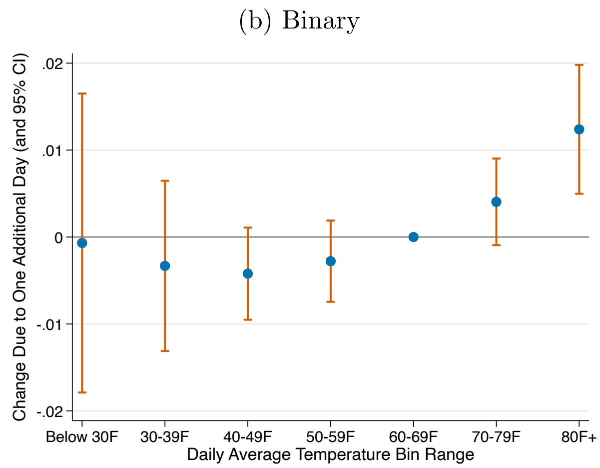
4 Results

Figure 4 shows OLS results from equation (1). The plot presents the outcome of daily violent acts as both a continuous count of occurrences in Panel (a) and a binary indicator for any occurrence in Panel (b), with coefficient estimates and 95% confidence intervals. In both cases, only the hottest temperature bin is statistically different from the baseline temperature range. The continuous specification shows a statistically significant 0.03 additional violent acts on days with average daily temperature in the 80F+ bin, compared to days that are 60-69F. The binary specification shows an 80F+ day means a statistically significant 1.1 percentage point increase in the probability of any violent infractions compared to moderate

[14] Judicial expert William Sturgeon notes that "prison populations will often become 'antsy, angry, sad and remorseful' around [holidays]" (The Washington Times, Dec. 10, 2014, by Phillip Swarts).

Figure 4: Impact of an Additional Day in the Average Temperature Range on Violent Acts Relative to 60-69F





Notes: Coefficient estimates are from an OLS regression including indicators for average daily temperature falling in the indicated temperature range, with 60-69F as the omitted bin. We also plot 95% confidence intervals. Regressions include facility, year, and week of year fixed effects, as well as facility-specific linear time trends and controls for daily rainfall. Counts use the number of violent acts per day as the outcome, while binaries use an indicator for any violent act in a given day. We cluster standard errors at the level of facility by calendar month.

days. Appendix Figure A-2 shows similar patterns emerge when we aggregate weather data using GHCN data by county (Panel (a)) or facility (Panel (b)).

We also re-estimate our model grouping lower temperature ranges (with no statistically or economically significant differences) and further splitting upper temperature ranges. Appendix Figure A-3 uses below 70F as the omitted group, testing for effects using average temperature in bins of 70-74F, 75-79F, 80-84F, and 85F and above. Results support that effects happen mostly on days where the temperature averages 80F and above, and while the coefficients on 80-84F and 85F+ days are not statistically different from each other, the magnitudes suggest that the hottest days have the largest effects. Appendix Figure A-4 shows a cubic spline model and approximate 95% confidence intervals, centered at 65F as the baseline rate and knots every 10F from 30-90F. This yields a similar shape, with rapidly increasing temperature effects beginning at approximately 80F.

For simplicity of exposition and expansions, we now replace indicator bins with a sole indicator for 80F or above, making all cooler temperatures the baseline omitted group:

$$y_{f,t} = \alpha_a^i + \theta_w^i + \omega_f^i + \lambda_f^i * t + \delta_1^i rain_{c,t} + \delta_2^i rainsq_{c,t} + \beta^i (T \in 80F+)_{c,t} + \epsilon_{f,t}^i, \tag{2}$$

where the i superscript indicates the coefficients can vary from those in equation (1). Table 1 shows results from equation (2). We begin discussion with Panel (a), which shows estimates on the count of violent acts. The mean of this dependent variable is 0.097, with a standard deviation of 0.58.

The coefficient on days with an average temperature 80F+ is 0.015 in Column 1, which contains only facility and year fixed effects, and in Column 2, which adds rainfall controls. Given our baseline mean, this implies that a facility day averaging 80F+ contains 16% more violent acts compared to a day averaging 79F or below. In Column 3, we add week of year fixed effects, and in Column 4, we add facility-specific linear time trends. The coefficient of interest increases to 0.020 in both specifications, implying an effect size of around 20%. In all specifications, results for hot days are statistically significant with $p < 0.01$.

Panel (b) of Table 1 reports regression estimates using a linear probability model (LPM) with the binary outcome of whether there was any violent act in the facility on a given day. This allows us to consider the extensive margin of violent behavior and is less subject to potentially outlier events involving many individuals (resulting in a reported incident for each involved inmate). The mean of this variable is 0.05, with a standard deviation of 0.22. The coefficient on days averaging 80F+ is 0.005 in Columns 1 and 2, with $p < 0.05$. The estimate increases to 0.009 in Columns 3 and 4 with $p < 0.01$. Week of year effects play an important role here, with the total effect starting at a 0.4 percentage point (8% of mean) increase in the first two columns and rising to a 0.9 percentage point (18% of mean) effect in the final two. This is possibly due to the "holiday" effect mentioned earlier, as many relevant US holidays driving increased violence occur in colder times of the year.

Appendix Table A-2 repeats Column 4 of Table 1 with altered standard error methods.

Table 1: OLS Estimates of Count and Occurrence of Violent Acts

	(1)	(2)	(3)	(4)
Panel (a): Count				
Avg. Temp 80F+	0.015***	0.015***	0.020***	0.020***
	(0.006)	(0.006)	(0.007)	(0.007)
Dep. Variable Mean	0.096	0.096	0.096	0.096
Panel (b): Binary				
Avg. Temp 80F+	0.005**	0.005**	0.008***	0.009***
	(0.002)	(0.002)	(0.003)	(0.003)
Dep. Variable Mean	0.050	0.050	0.050	0.050
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	No	Yes	Yes	Yes
Week of Year FE	No	No	Yes	Yes
Facility Trends	No	No	No	Yes
Clusters	432	432	432	432
Observations	92,052	92,052	92,052	92,052

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Outcome in Panel (a) is count of violent acts at the facility-day level. Outcome in Panel (b) is the binary indicator for any act of violence at the facility-day level. Bottom rows indicate fixed effects and controls in each regression. Data span 2004-2010. Temperature values estimated at the county level using PRISM weather data. We cluster standard errors at the level of facility by calendar month.

Panel (a) shows results for the count of acts, while Panel (b) shows results for the LPM. We show just the p-value from a test of statistical significance on the "80F+" coefficient. Column 1 clusters standard errors by county, given common temperature assignment for facilities within counties. Column 2 uses a Wild bootstrap, stratified at the county level with 10,000 replications, to address the possible issue of just 29 clusters in Column 1 (Cameron and Miller, 2015). Clustering at the county level gives the count model a p-value of 0.045 with bootstrapping, and 0.053 without. For the LMP, respective p-values are 0.014 and 0.007.

5 Robustness

We first re-estimate the results of Table 1 for the subsample of only larger correctional facilities, those with a realized capacity greater than 500 inmates, our 8 largest facilities. We do so to reduce noise that smaller facilities might contribute in the estimation. Among larger facilities, the average facility-day count of violent acts is 0.43, and the related binary outcome has a mean of 0.22. Appendix Table A-3 shows these results. Though coefficient magnitudes are larger, implied relative effect sizes are approximately the same as those in the main analysis due to higher baseline rates and counts at larger correctional facilities. As an alternate test for the role of facility size, Appendix Table A-4 repeats Table 1 using acts per 1,000 prisoners as the outcome, weighted by daily facility population. Effects remain statistically and economically significant. An 80F+ day increases rates by 0.036 violent acts per 1,000 facility population, an increase of approximately 20% of the mean rate of 0.176, in line with our main estimates.[15] We also re-estimate equation (2) with a more flexible series of time effects. Appendix Table A-5 repeats our main model with variations in time and region fixed effect interactions. In all cases, for both counts and our binary LPM, results are effectively unchanged.

We next re-estimate the outcomes in Table 1 using nonlinear models. We use a Poisson model for the count in Panel (a) and a logit model for the binary outcome in Panel (b). Results are in Appendix Table A-6, and Appendix Figure A-5 shows the analog coefficient graphs. The Poisson model suggests an impact of 0.20 on the 80F+ category. Interpreting this as a semi-elasticity, and using our baseline of approximately 0.1 acts, this is an increase of around 0.03 acts. The logit estimate is 0.30 for the coefficient on 80F+, which translates to a marginal increase of 0.012 percentage points.[16] Thus, nonlinear models arrive at similar conclusions in terms of sign, magnitude, and statistical significance.

Even after controlling for region and time fixed effects, unobserved factors may correlate

[15] In 2008, Mississippi passed a law designed to reduce prison overcrowding. Appendix Section D-1 shows this policy had little effect on the heat and violence relationship.

[16] We obtain this using the "margins" command in Stata 15.

with both violence and heat at the daily level. To test for such effects, we conduct two placebo tests of timing of hot days. The dependent variable is the count of violent acts in a given day, following the setup of Column 4 in Panel (a) of Table 1.[17] We first shift each day's temperature observation within facility forward or backward by up to 28 days, and re-estimate our regression. Panel (a) of Figure A-6 shows the coefficients from nine different regressions, ranging from "shifted backward 28 days" (-28) to "shifted forward 28 days" (+28) and including the true observation, which we notate with "0". We only observe statistically and economically significant effects when the indicator is assigned to the true date. As an extreme case, we next randomly reassign all 80F+ days across time and location 1,000 times and re-estimated equation (3) for each simulated dataset. Panel (b) of Figure A-6 shows the distribution of the 1,000 regression coefficients as the kernel density, and the "true" estimate, shown by the vertical line. Our estimate is far to the right of the placebo distribution of timing estimates, which are centered at zero.

6 Additional Considerations

6.1 Nonviolent Incidents

There are other possible incident reports in our data, ranging from our extreme cases to basic minor infractions such as refusing to make one's bed. Here we consider the nonviolent incidents (including what we call "aggressive behavior", which are less extreme cases of aggression such as threatening another or a fight without injury), addressing three policy and mechanism questions. First, while these are less socially costly events, they still represent additional conflict within the prison system. Second, if heat makes guards, on the margin, more likely to generally report incidents, or shifts guard absenteeism, nonviolent data should reflect this as well. Third, if heat alters how guards treat prisoners and increases general conflict, it could show up in less extreme interactions.

[17] The new regression equation is given by:

$$y_{f,t} = \alpha_a^{ii} + \theta_w^{ii} + \omega_f^{ii} + \lambda_f^{ii} * t + \delta_1^{ii} rain_{c,t} + \delta_2^{ii} rainsq_{c,t} + \beta^{ii}(\text{False T} \in 80F+)_{c,t} + \epsilon_{f,t}^{ii}, \quad (3)$$

where the superscript ii again indicates coefficients can vary from prior equation models.

Appendix Figure A-7 shows no other infraction or incident categories have patterns indicating effects of hot days. We show results for four other large categories covering all other incidents: aggressive behavior (omitting our cases of more extreme violence), refusing to work, inciting a riot or demonstrating, and general disobedience. In each case, we reproduce our semi-parametric coefficient graph, using both count of occurrences and the LPM. While some count results are negative and statistically different from zero in lowest average temperature ranges (a rare occurrence in our data), none of the LPM models have any statistically significant effects. There are two suggestive results of note. First, while no coefficient in aggressive behavior is statistically significant, the coefficients on the upper temperature values are positive and show a pattern similar to more extreme violent acts, particularly in the LPM. Second, general disobedience has suggestively-sized negative economic effects, though none are statistically significant. One possibility is that increases in violent acts represent an escalation of otherwise nonviolent infractions or incidents absent higher heat, meaning some of our additional violent acts "replace" less dangerous disobedience outcomes.

6.2 Cumulative Effects

It is possible that, while we observe violent acts on a specific day, the outcome is the result of buildup across several days of intense heat. Repeated hot nights driving poor sleep, for example, could escalate what would have been a less serious altercation into a violent act, giving heat a "cumulative" effect. To test if such effects exist in our data, we conduct three separate analyses of heat buildup. Appendix Table A-7 shows results, based on our model with year, week of year, and facility effects with facility-specific linear time trends. Our outcome is the count of violent events, and treatment is an indicator for temperature 80F+.

In Column 1, we include a variable with the count of days in the prior week that were also over 80F, which we also interact with our main indicator. This allows today's temperature to have an effect that may be higher or lower depending on the number of days in the past week that were also hot. Neither the "days in the last week" variable nor its interaction are economically or statistically significant, and their joint significance has a p-value of 0.91. We then try controls for spans of consecutive days. Column 2 shows indicators for consecutive days of 80F+, ranging from two to five. No indicators beyond our main coefficient of interest are statistically or economically significant, and the joint test of all lagged cumulative indicators yields a p-value of 0.88. Both modifications suggest that temperature on the day of the event plays a much larger role than any prior days or overall cumulative effects.

We also examine temporal displacement of violence, to test if hotter days shift rather than increase violent acts. If an inmate was planning to instigate a violent act, perhaps the temperature-aggression relationship moves that planned event earlier. To test this hypothesis, we aggregate results to the weekly level, including "number of 80F+ days in the week" as our regressor of interest, with number of violent acts in the week as the dependent variable. Results in Column 3 show that each 80F+ average temperature day in a week increases weekly violent acts by 0.018 (with a p-value of 0.058), which is very close to our initial daily estimate of 0.02, and in line with increases rather than shifts of violence.

7 Estimating Additional Violence due to Lack of Temperature Control

Our analysis implies that unmitigated exposure to days with temperature averaging 80F+ cause an additional 44 violent acts per year across the inmate population in our data. To derive this number, we use the estimates per 1,000 prisoners from Column 4 of Appendix Table A-4, where an additional day with temperatures 80F+ causes an additional 0.04 violent acts per 1,000 prisoners. We multiply this estimate by the daily number of prisoners in each facility on days they experience with temperatures of 80F+.

Extrapolation of estimates to the entire US requires substantial assumptions, including: (1) the Mississippi incarcerated population is representative of the US incarcerated population, and (2) none of the incarcerated individuals in the US have access to climate control sufficient to negate effects. With these in mind, we construct a nationwide estimate by first collecting data for all incarcerated individuals in the US, using the Correctional Facility

Locator from the Prison Gerrymandering Project.[18] This dataset identifies all correctional facilities counted in the 2010 Census, along with their associated county and an estimated facility population as of 2010. We match these facilities to the PRISM county-level weather data for 2010, and aggregate to county-level totals of incarcerated individuals. This allows us to find the number of incarcerated individuals on a given day in 2010 experiencing county-level temperature estimates of 80F+. These data suggest that in 2010, there were 110 million prisoner-days in the 80F+ range. Based on 0.04 additional violent acts per 1,000 prisoners, unmitigated heat could generate an additional approximate 4,000 violent acts per year in correctional facilities nationwide.

8 Conclusion

We demonstrate a link between intense heat and intense violence among the incarcerated in the Mississippi correctional system. A day with an average temperature above 80F raises both the count of daily violent acts and the probability of any violent act by approximately 20% of baseline. Our results identify heat's effect on inmate violence, an important link addressing a constitutional issue on which there is little empirical study. Heat (especially in the midst of climate change, which has steadily increased temperatures in many parts of the country) is relevant in considering the geographic placement of inmates in the US. Our finding that hotter days drive increased violence suggests significant returns to providing temperature control in correctional facilities. These effects can have important downstream consequences for both the inmates perpetrating violence and their victims. For example, inmates pushed to commit violent acts are more likely to experience delayed release, harsher prison conditions, or new criminal sentences. Chen and Shapiro (2007) show that harsher prison conditions (such as those we document here) increase recidivism, which means that what appear to be cost-saving measures such as foregoing A/C might unintentionally increase net social costs through longer and repeated prison sentences. There are potential welfare gains from reducing exposure to heat in prison, from both a constitutional and fiscal

[18] Available at https://www.prisonersofthecensus.org/locator2010/ as of April 26, 2021.

perspective, and our research highlights the social costs resulting from a captive population without the ability to mitigate heat.

We add to the growing body of literature showing that exposure to unmitigated high temperatures has detrimental effects on social well-being, including increased mortality and medical costs, losses in labor productivity, and decreased cognition.[19] Mounting evidence suggests that high temperatures also increase violent and criminal activity, but many studies encounter common identification challenges: avoidance and mitigation behavior, observation and recording bias, and resource/income effects. Our study presents an environment devoid of these common endogenous confounders. All correctional facilities in our data lack temperature control for inmates across the time of our analysis, meaning mitigation is limited, and prisoners are similarly limited in their ability to alter their daily routines. The highly structured prison environment minimizes the issue of recording and reporting bias, as all prisoners and guards must be present in the facilities regardless of temperature, and the lack of gainful in-facility employment options remove income effects. Thus, our estimates represent a more direct effect of heat on violence than many other settings.

If our findings extend to a non-incarcerated population, they suggest that the net effect of climate warming on global violence is positive. We find that while intensely hot days increase violence, very cold days do not have such an effect. This implies that increased violence in areas where the probability of hot days is rising is not offset by a drop in violence in areas that may experience fewer cold days. The extent to which regions can adapt to rising temperatures will play a large role in their ability to reduce these effects. As Heutel, Miller and Molitor (2020) note, regional infrastructure can make adaptation more or less difficult, and the US should expect the detrimental effects of increased heat will be larger in the Northeast, where infrastructure is designed to address issues of cold, and less problematic in the South, which has long dealt with higher temperatures. Such adaptation will not be

[19] For an overview of recent economics work on temperature, health, and productivity, see Heal and Park (2016). For recent examples of temperature, cognition, and learning, see Park et al. (2020), Park (2020) and Garg, Jagnani and Taraz (2020).

readily feasible, however, for those lacking temperature control infrastructure.

To some degree, our estimates also extend to the large share of the world population without access to direct temperature control. While prisoners are not a representative population in many aspects, the limited ability to adjust to uncomfortable climate is much more widespread. As recently as 2018, 40% of households in China did not have A/C. That number is over 80% in Mexico and Brazil, and around 95% in India (International Energy Agency, 2018). Our results indicate billions of people worldwide face temperature conditions conducive to increased violence.

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A-1 Additional Exhibits

Table A-1: Summary Statistics

	(1)
Share of Facility-Days by Bin	
Under 30F	0.008
	[0.086]
30-39F	0.058
	[0.235]
40-49F	0.139
	[0.346]
50-59F	0.173
	[0.378]
60-69F	0.185
	[0.389]
70-79F	0.265
	[0.441]
80F+	0.172
	[0.377]
Violent Outcomes	
Violent Acts per Day	0.096
	[0.564]
Prob. Violent Act	0.050
	[0.217]
Facilities	36
Counties	29
Observations	92,052

Notes: Table reports means with standard deviations in brackets. Data span seven years from 1/1/2004 to 12/31/2010.

Table A-2: Inference from Alternate Standard Error Estimation

	(1) County Level	(2) County level: Wild Bootstrap
Panel (a): Count		
p-value on Avg. Temp 80F+	0.053	0.045
Panel (b): Binary		
p-value on Avg. Temp 80F+	0.014	0.007

Notes: All estimates done using OLS. Estimates follow Column 4 of Panel (a) of Table 1, but with different standard error methods. Column 1 clusters at the county level. Column 2 performs a wild bootstrap, stratified at the county level, using 10,000 replications and Rademacher weights.

Table A-3: Estimates of Count and Occurrence of Violent Acts: Larger Facilities Only

	(1)	(2)	(3)	(4)
Panel (a): Count				
Avg. Temp 80F+	0.066***	0.065***	0.085***	0.085***
	(0.025)	(0.025)	(0.029)	(0.030)
Dep. Variable Mean	0.405	0.405	0.405	0.405
Panel (b): Binary				
Avg. Temp 80F+	0.020**	0.020**	0.034***	0.035***
	(0.009)	(0.009)	(0.011)	(0.012)
Dep. Variable Mean	0.207	0.207	0.207	0.207
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	No	Yes	Yes	Yes
Week of Year FE	No	No	Yes	Yes
Facility Trends	No	No	No	Yes
Clusters	96	96	96	96
Observations	20,456	20,456	20,456	20,456

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is limited to facilities with a minimum monthly population of 500. Outcome in Panel (a) is count of violent acts at the facility-day level. Outcome in Panel (b) is the binary indicator for any act of violence at the facility-day level. Bottom rows indicate fixed effects and controls in each regression. Data span 2004-2010. Temperature values estimated at the county level using PRISM weather data. We cluster standard errors at the level of facility by calendar month.

Table A-4: OLS Estimates of Violent Acts per 1,000 Prisoners

	(1)	(2)	(3)	(4)
Avg. Temp 80F+	0.027***	0.027***	0.035***	0.036***
	(0.009)	(0.009)	(0.011)	(0.011)
Dep. Variable Mean	0.176	0.176	0.176	0.176
Clusters	432	432	432	432
Observations	91,961	91,961	91,961	91,961

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates follow Panel (a) of Table 1, with two changes: (1) the dependent variable is scaled to reflect the count of violent acts per 1,000 prisoners, and (2) the regressions weight by facility daily population. We cluster standard errors at the level of facility by calendar month.

Table A-5: OLS Estimates of Count and Occurrence of Violent Acts – Alternate Fixed Effects

	(1)	(2)	(3)
Panel (a): Count			
Avg. Temp 80F+	0.018***	0.019***	0.014**
	(0.007)	(0.007)	(0.007)
Panel (b): Binary			
Avg. Temp 80F+	0.007***	0.008***	0.005*
	(0.003)	(0.003)	(0.003)
Facility FE	Yes	No	No
Week of Year FE	No	Yes	No
Year by Month FE	Yes	Yes	No
Facility by Month FE	No	Yes	No
Facility by Year FE	No	Yes	No
Facility by Month by Year FE	No	No	Yes
Clusters	432	432	432
Observations	92,052	92,052	92,052

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Outcome in Panel (a) is count of violent acts at the facility-day level. Outcome in Panel (b) is the binary indicator for any act of violence at the facility-day level. Bottom rows indicate fixed effects and controls in each regression. Data span 2004-2010. Temperature values estimated at the county level using PRISM weather data. We cluster standard errors at the level of facility by calendar month.

Table A-6: Nonlinear Model Estimates of Count and Occurrence of Violent Acts

	(1)	(2)	(3)	(4)
Panel (a): Count (Poisson)				
Avg. Temp 80+F	0.155***	0.153***	0.202***	0.200***
	(0.050)	(0.050)	(0.056)	(0.056)
Dep. Variable Mean	0.096	0.096	0.096	0.096
Clusters	432	432	432	432
Observations	92,052	92,052	92,052	92,052
Panel (b): Binary (Logit)				
Avg. Temp 80F+	0.138**	0.138**	0.229***	0.229***
	(0.057)	(0.057)	(0.071)	(0.071)
Dep. Variable Mean	0.053	0.053	0.053	0.053
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	No	Yes	Yes	Yes
Week of Year FE	No	No	Yes	Yes
Facility Trends	No	No	No	Yes
Clusters	408	408	408	408
Observations	86,938	86,938	86,938	86,938

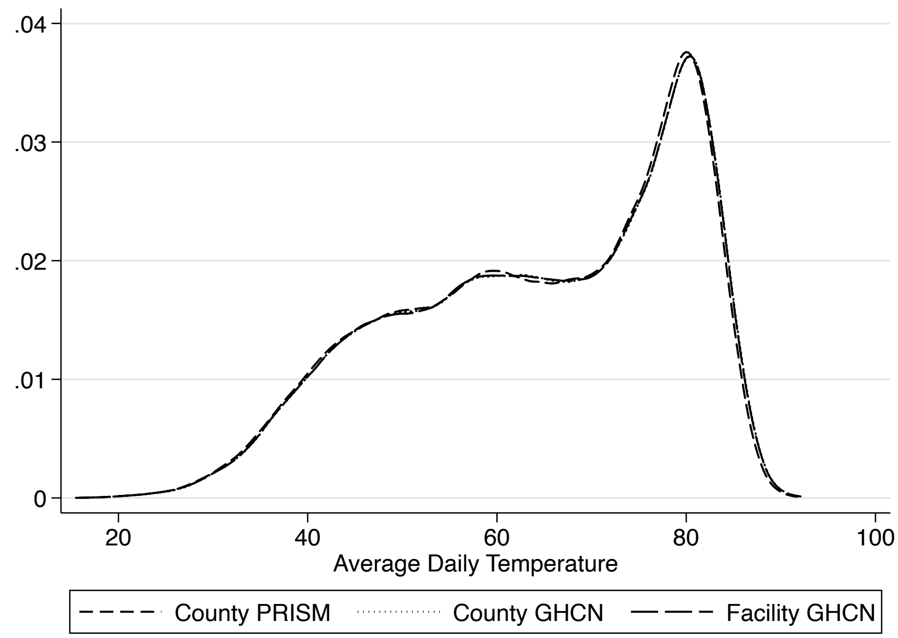
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Outcome in Panel (a) is count of violent acts at the facility-day level, which we estimate using a Poisson count model. Outcome in Panel (b) is the binary indicator for any act of violence at the facility-day level, which we estimate using a logit model — clusters and observations vary across models, as the logit does not estimate effects for facilities with zero violent acts across the period. Bottom rows indicate fixed effects and controls in each regression. Data span 2004-2010. Temperature values estimated at the county level using PRISM weather data. We cluster standard errors at the level of facility by calendar month.

Table A-7: Tests for Cumulative Effects

	(1)	(2)	(3)
	Daily Count		Weekly Count
Avg. Temp 80F+	0.022**	0.028**	
	(0.011)	(0.011)	
# of Avg. Temp 80F+ Days Last Week	-0.001		
	(0.002)		
Avg. Temp 80F+ X	-0.000		
# of Avg. Temp 80F+ Days Last Week	(0.003)		
Avg. Temp 80F+ for Last 2 Days		-0.012	
		(0.015)	
Avg. Temp 80F+ for Last 3 Days		0.009	
		(0.016)	
Avg. Temp 80F+ for Last 4 Days		-0.003	
		(0.020)	
Avg. Temp 80F+ for Last 5 Days		-0.005	
		(0.017)	
Avg. Temp 80F+ (Weekly Count)			0.018**
			(0.009)
Joint Test p-value	0.901	0.863	.
Observations	91,800	92,052	13,104

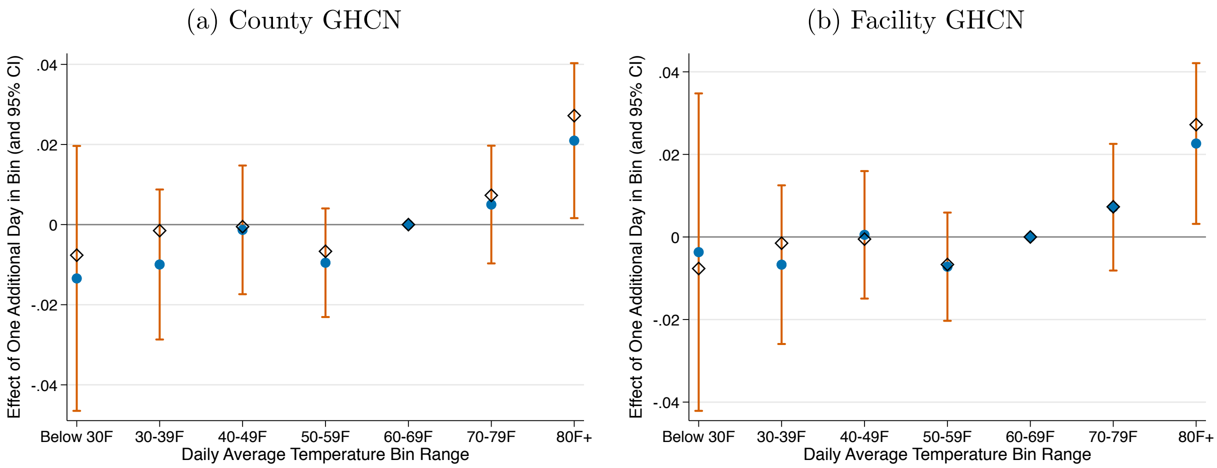
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models follow the fixed effects setup of Column 4 of Table 1. Column 1 adds the count of days with 80F+ in the past 7 days, plus an interaction between the indicator for 80F+ and the count of days 80F+ in the last 7 days. Column 2 includes indicators for number of consecutive days, leading up to the current day, with 80F+. In each case, we include the p-value of the test of joint significance for the additional cumulative control variables. Column 3 provides results at the weekly level, where we sum both counts of violence and days of 80F+ within a calendar week. We reestimate our initial model, replacing prison trends by day with prison trends by week. We cluster standard errors at the level of facility by calendar month.

Figure A-1: Temperature Distribution for Various Average Temperature Construction Methods



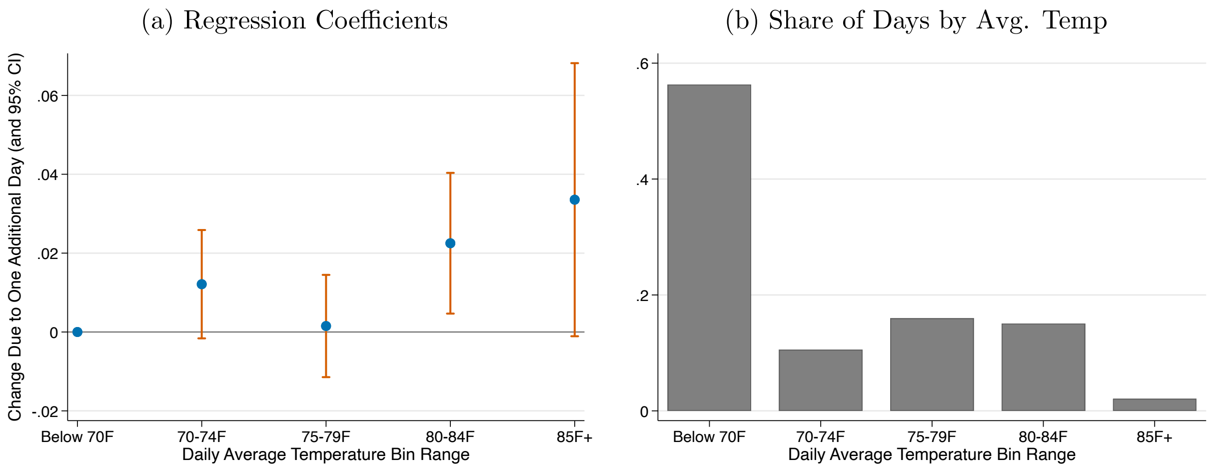
Notes: Distributions are average temperatures, at the indicated level, in the 2004-2010 period of our data. "County PRISM" refers to PRISM weather data aggregated to the county level. "County GHCN" refers to the NOAA Global Historical Climatology Network series of weather stations, aggregated to the county level using all monitors within 50 miles of a county centroid and weighted by $1/distance$. "Facility GHCN" refers to the NOAA Global Historical Climatology Network series of weather stations, aggregated to the facility level using all monitors within 50 miles of a prison location based on reported address and weighted by $1/distance$. We cluster standard errors at the level of facility by calendar month.

Figure A-2: Count of Violence Regression Coefficients by Temperature Bin Using Alternate Temperature Measures



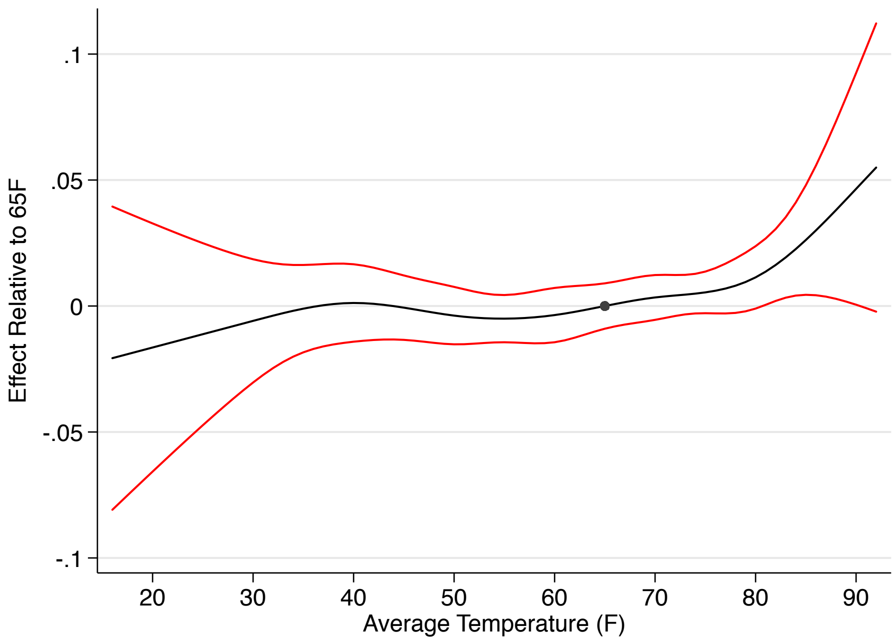
Notes: Coefficient estimates marked with filled circles are from a regression including indicators for average daily temperature falling in the indicated temperature range, with 60-69F as the omitted bin, and include 95% confidence intervals. Empty diamond markers show estimates from our main model using county-level PRISM data. Regressions include facility, year, and week of year fixed effects, as well as facility-specific linear time trends and controls for rainfall. Counts use the number of violent acts per day as the outcome. "County GHCN" refers to the NOAA Global Historical Climatology Network series of weather stations, aggregated to the county level using all monitors within 50 miles of a county centroid and weighted by $1/distance$. "Facility GHCN" refers to the NOAA Global Historical Climatology Network series of weather stations, aggregated to the facility level using all monitors within 50 miles of a facility location based on reported address and weighted by $1/distance$. We cluster standard errors at the level of facility by calendar month.

Figure A-3: Impact of an Additional Day in Average Temperature Range on Violent Acts Relative to Below 70F — Finer Upper Range Cuts



Notes: Panel (a) shows coefficient estimates from a regression including indicators for average daily temperature falling in the indicated temperature range, with below 70F as the omitted bin, and include 95% confidence intervals. Regressions include facility, year, and week of year fixed effects, as well as facility-specific linear time trends and controls for rainfall. Counts use the number of violent acts per day as the outcome. Panel (b) shows the average share of days in each relevant bin per year. We cluster standard errors in both panels at the level of facility by calendar month.

Figure A-4: Impact of Average Daily Temperature on Violence, Relative to 65F: Cubic Spline

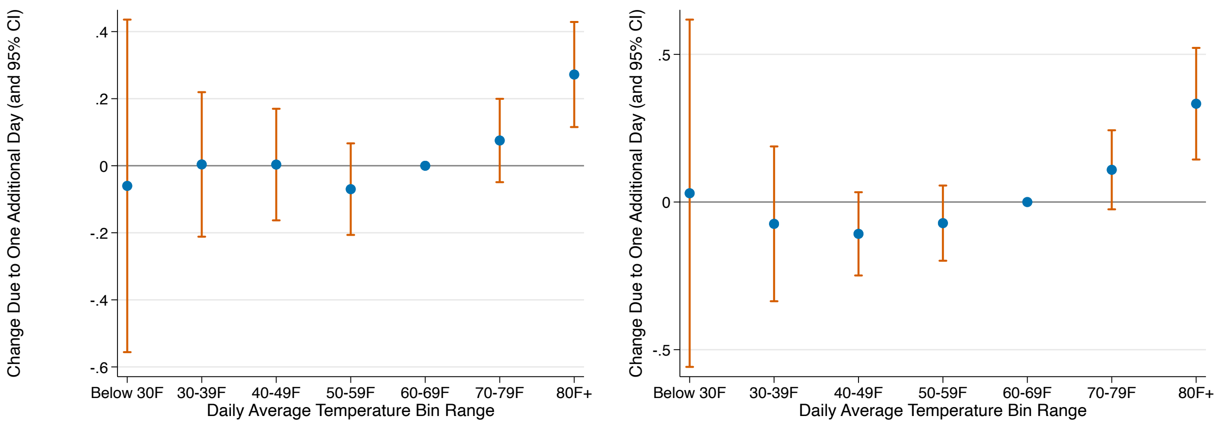


Notes: The plotted estimate is the predicted number of violent events relative to those predicted to occur at a temperature of 65F, and include 95% confidence intervals of the prediction in red. We base this prediction off a cubic spline regression, with knots at each 10F degree point from 30F to 90F. Regressions include facility, year, and week of year fixed effects, as well as facility-specific linear time trends — we omit controls for rainfall to facilitate graphing predicted effects. We cluster standard errors at the level of facility by calendar month.

Figure A-5: Nonlinear Regression Coefficients by Temperature Bin

(a) Poisson Count Model

(b) Logit Binary Model

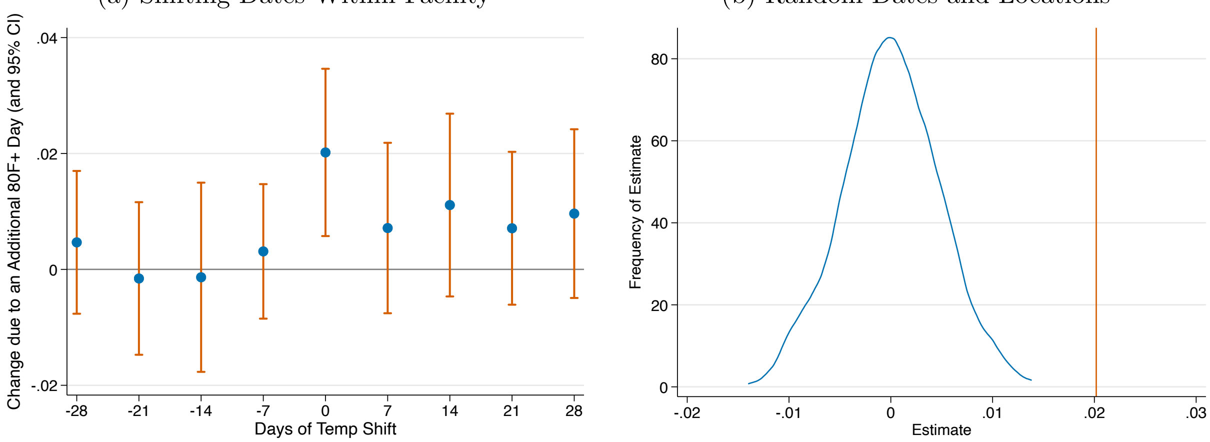


Notes: Coefficient estimates are from a regression including indicators for average daily temperature falling in the indicated temperature range, with 60-69F as the omitted bin, and include 95% confidence intervals. Regressions include facility, year, and week of year fixed effects, as well as facility-specific linear time trends and controls for rainfall. Counts use the number of violent acts per day as the outcome, which we estimate using a Poisson model. Binary uses an indicator for any violent act in a given day, which we estimate using a logit model. We cluster standard errors at the level of facility by calendar month.

Figure A-6: Falsification Tests

(a) Shifting Dates Within Facility

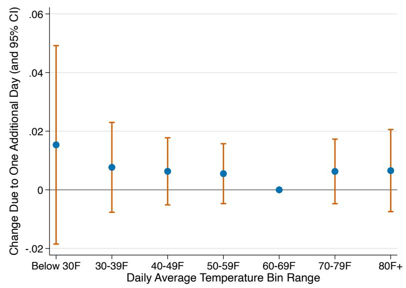
(b) Random Dates and Locations



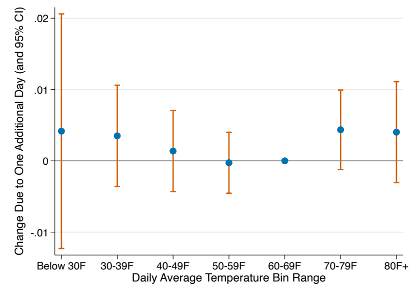
Notes: Panel (a) shows estimates from 9 separate regressions, with assignment of 80F+ days shifted forward or backward by the indicated number of days. Panel (b) shows the distribution of 1,000 regression estimates on random assignment of 80F+ days; the vertical line shows the estimate using the correctly assigned days. In all cases, regressions include facility, year, and week of year fixed effects, as well as facility-specific linear time trends and controls for rainfall. See Section 5 for details.

Figure A-7: Impact of an Additional Day in Average Temperature Range on Indicated Acts Relative to 60-69F

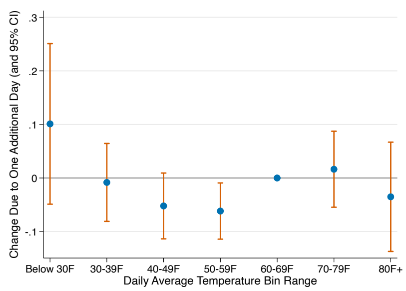
(a) Aggressive Behavior: Count



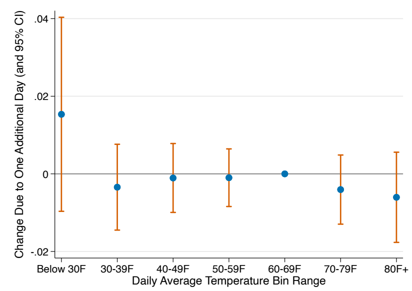
(b) Aggressive Behavior: Binary



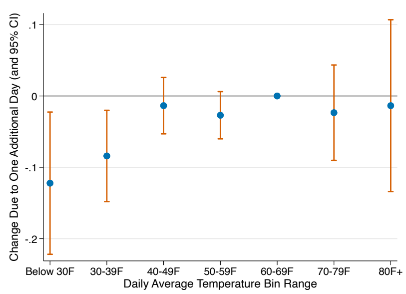
(c) Disobedience: Count



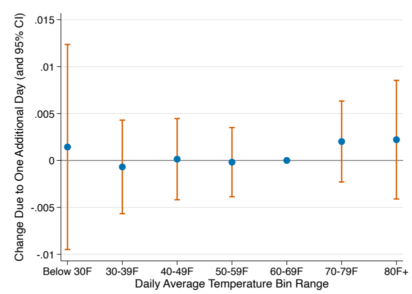
(d) Disobedience: Binary



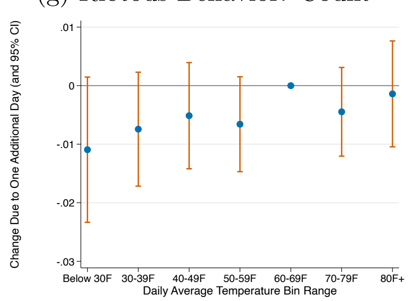
(e) Refusal to Work: Count



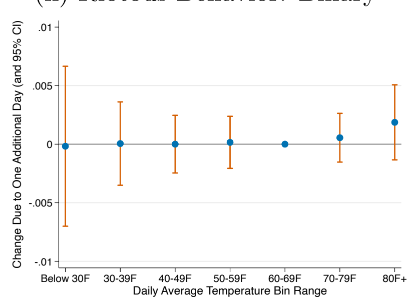
(f) Refusal to Work: Binary



(g) Riotous Behavior: Count



(h) Riotous Behavior: Binary



Notes: Regressions follow the LPM model in Panel (b) of Figure 4, but use alternative acts as the outcome of interest. Titles indicate relevant act. See Section 6.1 for details and Appendix B for categorization of different acts.

B-1 Incident Categorization

Incident category	Count	Incident category	Count
Violent		**Disobedience (continued)**	
Killing or assaulting anyone	4,560	Unauthorized possession money, etc.	565
Fighting, except self-defense	3,739	Failure to conform to grooming standards	535
Assaultive action against any person resulting in serious physical injury	1,367	Lying to an employee	502
Murder	2	Unauthorized possession of items	481
Total	*9,668*	Smuggling of contraband items into, out of, or within the institution	389
Aggressive Behavior		Unauthorized giving/accepting of money or anything of value	377
Threatening another	3,922	Making or drinking intoxicants	375
Physical action against another person (no serious injury)	1,862	Preparing/ conducting gambling	343
Setting a fire	1,081	Negligent or deliberate destruction, alteration or defacing of state, personal, or community property	304
Making threatening or intimidating statements	775	Tattooing or piercing self or others or allowing self to be tattooed or pierced	291
Deliberately or negligently causing a fire	304	Unauthorized contact with the public	265
Involvement in distruptive, assaultive, or criminal gang activity	250	Miscellaneous contraband	242
Inflicting injury to self (self-mutilation)	153	Violating the institutional dress code or grooming standards	230
Arrest for criminal activity while on 72-hour leave	7	Escape, attempting or planning	229
Total	*8,354*	Unauthorized communication with any member of the public, staff, or between inmates	221
Disobedience		Informal resolution	218
Refusing to obey staff order	28,001	Forging/ altering of articles	182
Engaging in sexual act	14,682	Pursuing or developing a relationship that is unrelated to correctional activities with a non-inmate	168
Unauthorized possession of contraband	10,986	Violations of mail, telephone, or visiting regulations	162
Unauthorized possession - drug/alcohol related	8,814	Improper or unauthorized use of state equipment or materials	148
Refusing or failing to obey an order of staff	8,025	Giving or receiving anything of value to or from another	134
Violate - conditions of release	7,578	Malingering/ feigning illness	124
Using abusive or obscene language	7,208	Bribing (offering to) staff	123
In unauthorized area w/o permission	7,204	Tampering with physical evidence or hindering an investigation	120
Not standing/ interfering with count	4,922	Unauthorized removal of food or untensils from any food service area	119
Unauthorized use of drugs or intoxicants or testing positive for either	4,718	Extortion	81
Possession of major contraband	4,465	Violating a condition of any outside work assignment	75
Inappropriate sexual behavior with another person or indecent exposure	4,442	Engaging in extoration or blackmail, bribery, loan sharking, collection, or incurring debt	73
Interfering with security	4,397	Unauthorized possession of utensils	65
Not following safety/ sanitation regulations	4,151	Refusing to submit to a search	62
Destroying property	3,717	Misuse of equipment, etc.	55
Abusive, disrespectful, vulgar, obscene or threatening language, gestures or actions	3,485	Gambling	49
Being in a restricted or unauthorized area	3,257	Escape	48
Failure to abide by the statement of conditions of release	2,666	Faking illness or injury	45
Possession serious contraband	2,318	Unauthorized possession of clothing	40
Being loud, boisterous or disorderly	2,301	Breaking or entering into another inmate's locker, room, cell, or living unit	38
Stealing	2,071	Absconding supervision for probation or parole	32
Refusing or failing to comply	1,902	Littering	31
Disruptive behavior or disorderly conduct which threatens the orderly running of the facility	1,737	Using mail to obtain money, goods, or services by fraud	14
Detention notice	1,686	*Total*	*162,681*
Providing false information	1,308	**Refusal to Work**	
Refusing or failing to submit to a drug urinalysis test	1,244	Refusing to work	13,614
Tattooing or self-mutilation	1,168	Refusing or failing to carry out work assignment	7,168
Attempting/violating miscellaneous offenses in Ch. 13, Articles 1-34	1,151	*Total*	*20,782*
Violation of phone, etc. Privileges	976	**Riotous Behavior**	
Failure to abide by any published institutional schedule or documented	963	Demonstrating/encouraging	1,270
Interfering with an employee in the performance of their duties	810	Rioting or encouraging others	171
Negligent or deliberate destruction, alteration or defacing of state, personal, or community property	771	Inciting to riot or rioting	169
Stealing	720	Nonviolent demonstration or inciting a nonviolent demonstration	94
Destroying or tampering with life safety equipment, locking or security	680	*Total*	*1,704*
Failure to clean bed area or pass bed area inspection	602	***Grand Total***	***203,189***

Notes: Table shows the number of incidents by the five analysis categories for inmates held by the Mississippi Department of Corrections between 2004 and 2010. Exhibit includes the universe of incidents in their original detail from the raw data extract.

C-1 Heat Index

The NOAA uses the following baseline equation to estimate the heat index:

$$\begin{aligned} HI &= -42.379 + 2.04901523 * T + 10.14333127 * RH - .22475541 * T * RH \\ &\quad -.00683783 * T * T - .05481717 * RH * RH + .00122874 * T * T * RH \\ &\quad +.00085282 * T * RH * RH - .00000199 * T * T * RH * RH, \end{aligned} \tag{C-1}$$

where T indicates temperature in Fahrenheit and RH is relative humidity, a measure of water vapor present in the air relative to maximum saturation at a given temperature. This is based upon a multiple regression analysis that Rothfusz (1990) describes in detail. When temperature falls between 80 and 87 Fahrenheit, and relative humidity is above 85%, we follow NOAA and modify the estimate by

$$Adjustment = \big((13 - RH)/4\big) * \sqrt{\Big(17 - \big|(T - 95.)\big|\Big)/17}. \tag{C-2}$$

Other adjustments may be necessary for ranges outside of the temperatures we consider in our analysis – for details, see Rothfusz (1990).

Our primary weather data do not include relative humidity. Such data are available for two temperature sensors in Mississippi in the daily U.S. Climate Reference Network (USCRN). To estimate the heat index, we first use the USCRN data to regress the minimum daily relative humidity on the maximum daily temperature across the year 2010. We use the minimum humidity given that as temperatures rise, relative humidity tends to decrease. This is a result of hotter air being able to hold more moisture, and relative humidity being a measure of water vapor in the air as the percentage of total possible saturation. This estimate suggests a one degree F increase in daily maximum temperature correlates with a 0.4% decrease in minimum daily relative humidity. We then use this to predict relative humidity in our PRISM data for any given daily maximum. We use the formula above to calculate a maximum heat index for each day in our data with average temperature over 80 degrees, using the maximum daily temperature and the regression-estimated humidity.

D-1 Population Effects and the Parole Policy of 2008

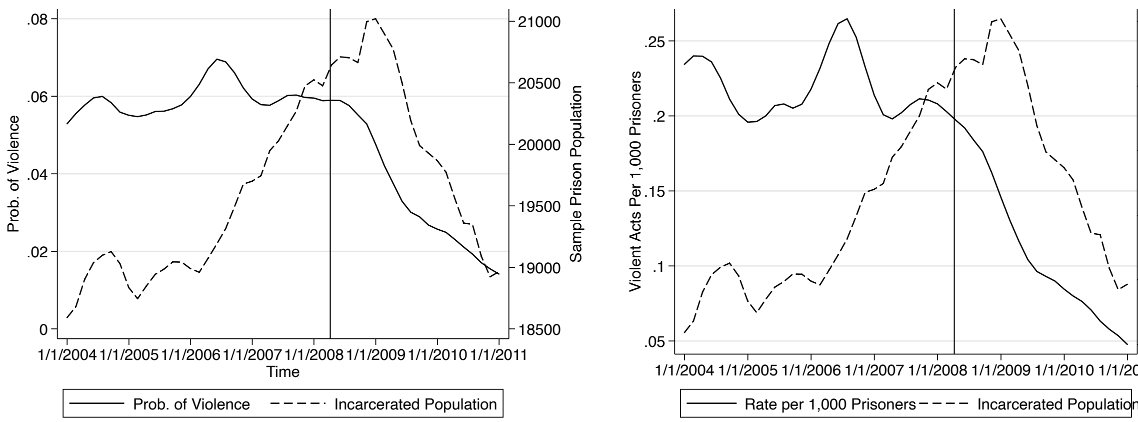
In 2008, the Mississippi Senate passed Senate Bill 2136, a substantial parole reform aimed at curbing the rising prison population. The bill brought forward parole eligibility for nonviolent and single-offense prisoners after serving 25% of their sentence, a decrease from 85%. The bill was signed into law April 7th, 2008, and applied to all new sentences and retroactively to all current sentences. The policy resulted in a marked decrease in the prison population, aligning with a decrease in prison violence. Panel (a) of Appendix Figure D-1 shows the trend in average acts per prisoner (solid line) and total facility population (dashed line). Panel (b) shows similar trends for the probability of any violent act. The vertical line indicates the date the Governor of Mississippi approved the bill, which coincides almost perfectly with a change in overall patterns of violent acts per prisoner. While this speaks to the link between facility population and violence, how it changed the heat-violence relationship remains an open question. With fewer inmates, there might be closer supervision of inmate conflict, or fewer opportunities for problematic interactions. Overcrowding might also contribute to any effects of heat, which is important from a policy perspective.

To test if reducing the prison population changed the relationship between temperature and violent acts, we allow the effect of hot days to vary by before and after the passage of the bill by interacting our temperature indicator with an indicator for post-April 7th, 2008. Table D-1 presents our results. Column 1 is the OLS count estimate, Column 2 repeats the OLS count estimate as per-prisoner, weighted by facility population, and Column 3 is our LPM. In each case, the interaction term with post-reform is not statistically different from zero, though across all models the total economic effect is smaller by about one-third post-bill. Reducing the number of inmates in prison appears to reduce violent acts, and may also reduce the impact of temperature on violent acts, but we lack the precision to specifically identify such effects.

Figure D-1: Counts and Probabilities of Violence Across Prison Reform

(a) Probability of Any Violent Act

(b) Acts per 1,000 Prisoners



Notes: Figures show trends in violent acts alongside incarcerated population for all prisoners in our sample. Panel (a) shows the binary indicator for the probability of any violent act at the facility-day level. Panel (b) shows the rate of violent acts per 1,000 population at the facility-day level. Vertical line indicates the signing of the Mississippi prison reform bill altering parole processes. See Section D-1 for details.

Table D-1: OLS Estimates of Differential Effects Across Parole Reform

	(1) Count	(2) Count per 1,000	(3) Binary
Avg. Temp 80F+	0.023**	0.040***	0.010***
	(0.010)	(0.014)	(0.004)
Avg. Temp 80F+ X Post Bill	-0.006	-0.010	-0.004
	(0.010)	(0.015)	(0.004)
Post Bill	-0.008	-0.016	0.002
	(0.019)	(0.032)	(0.005)
Observations	92,052	91,961	92,052

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models follow the fixed effects setup of Column 4 of Table 1. Post Bill refers to the period beginning on April 7th, 2008, when a parole reform bill passed and lessened requirements for parole consideration for a subset of Mississippi inmates. Column 1 is the OLS count of violent acts at the facility-day level, and Column 2 is the OLS count of violent acts per 1,000 prisoners at the facility-day level, weighted by facility population. Column 3 is the linear probability model of any violent act at the facility-day level. Observations in Column 2 are lower due to a small number of facility/day cells without recorded population. We cluster standard errors at the level of facility by calendar month.

E-1 Accounts of Extreme Heat in Correctional Facilities

Below are examples of reported accounts of heat in correction facilities.

> "I'd be in a cell for 23 hours a day and it was so hot in there I would put my hand to the wall and it would get burned."
>
> "There was no ventilation system so my cellmate and me would take turns sleeping on the floor. You'd clean the floor, throw water down so it was like a puddle and lie down on it on a sheet. Everything would be completely dry in the morning. The summers were just miserable."
>
> Milman, O. (2019, Jul 2). 'People are in danger': the prisoners feeling the effects of the US climate crisis. The Guardian.
>
> https://bit.ly/35sC0xu
>
> "The spokesperson said that inmates have "the ability to access water throughout the day" and that ice and water coolers are refilled continuously — contradicting the accounts of inmates who said that ice rations are often reduced and sometimes outright denied, that in some facilities they are given no ice or cold water for days at a time, that ice is so scarce that inmates will buy it off each other, and that inmates residing in a given cell block are given ice water to pass down the row of cells, which often leads to violence and hoarding of the vital resource."
>
> Speri, A. (2016, Aug 24). "Deadly Heat" in U.S. Prisons is Killing Inmates and Spawning Lawsuits. The Intercept.
>
> https://bit.ly/3pVipj7
>
> "It routinely feels as if one's sitting in a convection oven being slowly cooked alive. There is no respite from the agony that the heat in Texas prisons inflicts."

Jones, A. (2019, Jun 18) Cruel and unusual punishment: When states don't provide air conditioning in prison. Prison Policy. https://bit.ly/3gqtPbu

"Lance Lowry, a former prison guard in Texas who now works with the guards union, says the corrections officers have many of the same heat-sensitive health conditions as prisoners — obesity, diabetes, high blood pressure, even mental illness. "Officers frequently suffer from heat cramps and a lot of heat illnesses," Lowry says."

"Former Texas warden Keith Price, now a professor of criminology and sociology at West Texas A&M University, said that it's important to accommodate heat-sensitive prisoners, but that inmates also need to acknowledge that prison is not a five-star hotel. "You know, they don't get to go get a cheeseburger whenever they want to, either," Price said. "So, I mean, you know there's a certain amount of things that you give up when you become incarcerated"

Roth, Alisa. (2014, Jul 24) Do Heat-Sensitive Inmates Have A Right To Air Conditioning? National Public Radio. https://n.pr/3iHx2Vw

"However, one prisoner said the fans are sometimes turned off for punishment, and are taken away after September 1. In other cases, prisoners have reported being denied ice and cool showers during the summer months, while even in prison units that have air conditioning, staff have set thermostats at temperatures in the 80s."

Clarke, M. (2019, Oct 7) As Climate Changes, High Temperatures Plague Prisons and Jails. Prison Legal News. https://bit.ly/3gpBrLe

"Jeff Edwards, a plaintiffs lawyer in Austin, brought the class action suit involving the Pack Unit and is representing eight families whose loved ones died in hot prisons. They include Rodney Adams, a Dallas man sentenced to four years for driving while intoxicated who started convulsing shortly after arriving at the Gurney Unit in east Texas in 2012. He died less than two days after his arrival — his body temperature had reached 109.9."

> Chammah, M. (2017, Oct 11) "Cooking Them to Death": The Lethal Toll of Hot Prisons. The Marshall Project.
> https://bit.ly/3xrCPTd

"A surge in violence in Georgia prisons over the past few weeks has left at least two inmates dead and dozens of others injured, put staff in danger and forced the lock-down of as many as eight of Georgia's 33 prisons. Contributing to the dangerous climate inside the state's prisons have been the heat in prisons without air conditioning, the prevalence of cellphones that sell for as much as $500 in the hands of thousands of inmates (8,800 confiscated in the first six months of this year) and the growing presence of violent gangs that increased their numbers last year alone by an estimated 4,200."

> Cook, R. (2015, Aug 23) Georgia prisons: Gangs, rising violence, thousands of cellphones. The Atlanta Journal-Constitution
> https://bit.ly/3cIbJQ7