Temperature and Convictions: Evidence from India

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Abstract

High temperatures have been shown to affect human cognition and decision-making in a variety of settings. In this paper, we explore the extent to which higher temperatures affect judicial decision-making in India. We use data on judicial decisions from the Indian eCourt platform, merged with high-resolution gridded daily weather data. We estimate causal effects by leveraging a fixed effects framework. We find that high daily maximum temperatures raise the likelihood of convictions and these results are robust to numerous controls and specifications. Our findings contribute to a growing literature that documents that the negative impacts of rising temperatures are often more severe in low- and middle-income countries.

JEL codes: K37, K41, Q54.

Keywords: Temperature, Climate Change, Court Outcomes, India.

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1 Introduction

As climate change accelerates, human societies will be exposed to increased frequencies of extreme heat (Stocker et al., 2013). Existing research documents that these higher temperatures have significant negative impacts on human decision-making across a variety of settings. Higher temperatures have been linked to reductions in productivity (Behrer et al., 2021; Heyes and Saberian, 2022), changes in mood (Baylis, 2020; Denissen et al., 2008) and happiness (Rehdanz and Maddison, 2005), and to negative effects on decision-making, including in various areas of learning (Allen and Fischer, 1978; Hancock and Vasmatzidis, 2003), test performance (Park, 2022; Graff Zivin et al., 2018; Garg et al., 2020), and heuristics reliance (Cheema and Patrick, 2012).

One area of decision-making that is particularly high-impact is the decision-making of judges. Ludwig and Mullainathan (2021) assert that judicial decisions sometimes appear to be influenced by extraneous factors. In this paper, we explore extreme heat as an extraneous factor that could impact the conviction rate in the Indian judicial system. Using a large judicial panel dataset and a fixed effect approach, we find that extreme high temperatures increase the probability of convictions. India provides an especially crucial case study to explore the link between high temperatures and judicial decision-making because it is the world's largest democracy and a tropical country that frequently experiences extreme heat.

We take advantage of rich data on judicial decisions from the Indian eCourt platform.[1] These data cover the universe of district-level courts. We merge this dataset on judicial decisions with district-level daily temperature constructed from the ERA5 gridded weather data (Hersbach et al., 2020). The use of district-level data allows us to analyze our research question of interest at the most granular spatial resolution possible. Because we are interested in the impact of high temperatures on *judicial* decision-making, we focus our analysis on cases that end in either convictions or acquittals, which are the most harsh or lenient decisions a

[1] Ash et al. (2022) make data on judicial decisions, dates, defendant gender, criminal offenses, and court from this platform available upon request.

judge can make, and we define our conviction rate relative to this set of outcomes.[2]

We use a linear probability framework to estimate how maximum daily temperatures impact the probability of a conviction, conditional on controls for defendant demographics, weather and pollution characteristics, as well as time fixed effects, district fixed effects, and judge fixed effects. We explore three temperature specifications: a linear temperature specification, a threshold temperature specification, and a binned temperature specification. Our identifying assumption, common in the climate literature, is that conditional on our time, district, and judge fixed effects, the remaining variation in daily temperature is *as-good-as-random*, allowing for a causal interpretation of our estimates.

Across all three of our temperature specifications—linear, threshold, and binned—we find that higher temperatures lead to a statistically significant increase in conviction rates. For example, our threshold model specifically shows that on days with daily maximum temperature above 37.7°C (99.9°F), conviction rates increase by 1.1 percentage points, which is a 6.2% increase relative to the baseline conviction rate of approximately 18%.[3] Looking across different categories of crimes, we find that high temperatures increase conviction rates specifically for cases related to violent crimes. We also find evidence that the impacts of high temperatures on conviction rates are greater in courts with lower-quality infrastructure. We do not find evidence that the impact of higher temperatures on conviction rates is statistically significantly different for male versus female judges or for male versus female defendants.

Our findings are robust to several different specification variations such as: the inclusion of trial characteristic controls; an alternate definition of conviction rate; the use of different temperature thresholds; the use of different standard error clustering methods; the use of wet bulb globe temperature (WBGT), a composite measure that incorporates both temperature and humidity; and the inclusion of various sets of fixed effects.

Our findings show that rising temperatures in India increase the prevalence of harsh

[2]This means we exclude outcomes such as "plead guilty," which arise from defendant decision-making, rather than judicial decision-making.

[3]In our estimation sample, 6.4% of the judicial decisions were made on days on which the maximum daily temperature exceeded 37.7°C.

judicial outcomes for defendants in general. We are interested in judicial decision-making, which is why we focus on the outcomes of convictions and acquittals, which are ultimately the decision of the judges. However, it is important to note that the judges may be swayed by the behavior of witnesses, defendants and prosecutors on the day of the trial, and that these actors in turn may be influenced by high temperatures. Thus, we interpret our findings as general equilibrium effects given that we cannot ascertain from the data whether increases in conviction rates ensue directly from climate-driven effects on judges or whether judges are indirectly influenced by the climate-driven behavioral responses of witnesses, defendants, prosecutors, or some combination of these parties during trials.

We contribute to a small but growing literature that explores the impact of high temperatures on justice-related outcomes such as crime (Ranson, 2014), arrests (Behrer and Bolotnyy, 2022), police stops (Obradovich et al., 2018), prison violence (Mukherjee and Sanders, 2021), police-civilian interactions (Annan-Phan and Ba, 2020), and court decisions (Heyes and Saberian, 2019). The bulk of this literature focuses on the U.S. or other high-income countries, which suggests that studying India, a lower-middle income country, may present a valuable case study. Many low- and middle-income countries already face a higher baseline burden of high temperatures relative to high-income countries. Furthermore, they are projected to face earlier emergence of climate-change-induced heat extremes (Harrington et al., 2016).

Within the climate-justice literature, our study is closest in spirit to research that links judicial outcomes and high temperatures in Australia (Siminski and Evans, 2021), Texas (Behrer and Bolotnyy, 2022), and the United States in general (Heyes and Saberian, 2019; Spamann, 2022). First, our study makes an important contribution to the literature by focusing specifically on the Indian context. One reason we find significant impacts of temperature on judicial outcomes in India – relative to the null results found for Australia and the U.S. – might be because India has a significantly higher heat burden than the U.S. For example, in the U.S, only 0.3% of county-day observations have an average daily temperature that exceeds 90°F (Deschênes and Greenstone, 2011), whereas in India, our calculations show that more than 8% of the court decisions in our sample are rendered in a day with temperature that exceed this threshold. Therefore, we provide important insight into the impacts of high temperatures on court outcomes in a populous, lower-middle income country that is much more climate-vulnerable (Mendelsohn et al., 2006). By juxtaposing our findings with the earlier literature on developed nations, we hope to provide additional insight into the unequal burden climate change delivers across countries with differing levels of development.

Second, our study offers temporal differences in the analysis of criminal convictions. Even though Behrer and Bolotnyy (2022) and Siminski and Evans (2021) both evaluate criminal convictions, the procedural details of the Indian judicial system allow us to disentangle temperature effects on conviction outcomes from temperature effects on crime rates. Specifically, the court system in India is notorious for lengthy case backlogs. This backlog means that court decisions are separated temporally from the dates that crimes were committed. Estimates of the effect of temperature on convictions are thus unlikely to be conflated with temperature effects on crime rates or arrest rates.

Our results suggest that climate-induced increases in frequency of extreme heat may trigger further increases in the probability of convictions, especially for hot tropical countries like India. It is unlikely that this increase in judicial harshness is optimal given that extreme heat impairs cognitive performance (Graff Zivin et al., 2018; Krebs, 2022; Park, 2022), reduces productivity (Behrer et al., 2021), increases impatience (Carias et al., 2021), and makes more likely the occurrence of negative mood states, such as expressed sentiments (Baylis, 2020). Our estimates are relevant in the context of the climate change literature because they demonstrate yet another costly impact of rising temperatures, even in the potential presence of climate-control technology (Adhvaryu et al., 2020; Zhang et al., 2021; Yi et al., 2021).

The remainder of the paper proceeds as follows: Section 2 describes the potential mechanisms found in the existing literature that could link high temperatures to increased conviction rates. Section 3 discusses judicial decision-making in the Indian context. Section 4 describes the data and presents summary statistics of our estimation sample. Section 5 provides an overview of the empirical strategy. Section 6 discusses the main findings and sensitivity checks. Section 7 concludes.

2 Related Literature

In this section, we survey the potential mechanisms found in the existing literature that could cause higher temperatures to increase conviction rates in the Indian judicial system. First, we note that existing research has found that judges often make automatic, snap judgments that can sometimes lead to erroneous decisions (Guthrie et al., 2007). Furthermore, existing research demonstrates that judicial decision-making can be influenced by mood (Englich and Soder, 2009) as well as extraneous, external factors including the timing of the decision relative to food breaks (Danziger et al., 2011), the outcome of recent local sports games (Eren and Mocan, 2018), unrelated preceding court outcomes (Chen et al., 2016) television broadcasting of unrelated criminal justice events (Philippe and Ouss, 2018), judges' previous professional experience (Harris and Sen, 2022), and increased caseload levels (Shumway and Wilson, 2022).

Second, existing research has found that higher temperatures can lead to worse mood outcomes. In particular high temperatures have been linked to increases in aggression and hostility (Anderson et al., 1995), negative affect broadly construed (Denissen et al., 2008), destructive behavior (Almås et al., 2019), expressions of negative emotional sentiments (Baylis, 2020), and impatience (Carias et al., 2021), as well as decreases in willingness to help others (Cunningham, 1979) and self-reported happiness (Rehdanz and Maddison, 2005). Since earlier research shows that adverse external events (such as local sports game losses) lead to an increase in harsher judicial outcomes, it is plausible that negative mood states triggered by higher temperatures could lead to a similar increase in judicial harshness.

Third, it is important to note that high outdoor temperatures can have negative impacts on human mood and cognition, even when indoor temperatures might be climate-controlled. In particular, recent studies confirm that climate infrastructure does not completely alleviate the impact of rising outdoor temperatures. For example, Adhvaryu et al. (2020) find that higher outdoor temperatures reduce production line efficiency in indoor garment factories in Bangalore, India. Zhang et al. (2021) find that hot temperatures affect low-stakes cognitive activities in China even when air-conditioning is accounted for in the model. Yi et al. (2021) also conclude that outdoor heat stress negatively affects verbal cognitive performance in China despite the availability of air-conditioning.

Fourth, high temperatures in India may influence judicial outcomes despite the fact that previous work on the U.S. and Australia has found mixed impacts of temperature on judicial outcomes. Heyes and Saberian (2019) has found that higher temperatures reduced favorable outcomes in asylum cases in the U.S., but further work that extended the sample period of the dataset finds much negligible effects (Spamann, 2022).[4] Work on Texas (a comparatively hot state, relative to the overall climate of the U.S.) finds that on hotter days judges in Texas hand down longer prison sentences conditional on conviction (Behrer and Bolotnyy, 2022). Research on Australia finds no effect of outdoor temperatures on court case decisions (Siminski and Evans, 2021). However, it is likely that the impacts of high temperatures may differ across Australia or the whole U.S. versus India because of India's higher burden of heat.[5] In fact, the existing literature contains examples of studies that find that India's burden of heat is indeed significantly higher. For example, Johnston et al. (2021) fail to find a statistically significant impacts of higher temperatures in the previous year on cognitive

[4] Spamann (2022) refutes the evidence presented in Heyes and Saberian (2019) due to coding and data entry errors in the study; once the errors are corrected, the main result falls by about two-thirds.

[5] In the U.S, only 0.3% of county-day observations have an average daily temperature exceeding 90°F (Deschênes and Greenstone, 2011), while in India, more than 8% of our court decision observations exceed this threshold. In Australia, parts of the country are very hot, but the country's population is overwhelming concentrated in the milder regions (`http://sisgeographyigcsewiki.mrbgeography.com/population-distribution-and-density`). For example, in the sample of court cases in Siminski and Evans (2021), the average daily temperature is 64°F, whereas the average daily temperature for our sample of court cases in India is substantially higher: 79°F.

performance (as proxied by test scores) in Australia, whereas Garg et al. (2020) find that high temperatures in the previous year significantly decreases student test scores in India.

Fifth, there are specific features of the Indian judicial system, relative to the U.S. and Australia, which may exacerbate the impacts of high temperatures on judicial outcomes. Court infrastructure in India is of significantly lower quality than that of high income countries (Chandrashekaran et al., 2021).[6] Court infrastructure deficit may increase stress on judges and make them more susceptible to the influence of extraneous factors, such as temperature. Poor court infrastructure may also mean that Indian judges have comparatively less access to reliable high-quality climate control than judges in high-income countries. In addition to lower quality court infrastructure, the Indian judiciary faces a very significant backlog in cases (Times of India, 2010; Amirapu, 2021) and high case loads per court. This backlog may also increase judicial stress and make judges more susceptible to extraneous factors.

3 Institutional Detail

The Indian judicial system is comprised of three levels: district-level and subordinate courts (which fall under the purview of individual state governments), a High Court in each state, and a single federal Supreme Court. We focus on cases decided in the district-level and subordinate courts, because these are the case decisions that are included in the eCourts dataset.

In contrast to many high-income nations, in India judges wield significant power over the verdict of a case. Juries have been outlawed in India since 1959, giving presiding judges full agency over case outcomes (Jaffe, 2017). Notwithstanding, the Indian judicial system is still subject to bias, discrimination, and lack of representation. Women represent half of India's population but only 28% of its district judges (Ash et al., 2022). Judges have a significant margin of subjectivity in their rulings and research suggests that extraneous factors, such as

[6] See Appendix Figure A1 for two examples of Indian district court buildings.

the judge's background, can shape judicial decisions. For example, Bharti and Roy (2022) conclude that judges who were exposed to riots in their childhood are more likely to deny bail.

The court system in India is notoriously slow-functioning, with a substantial backlog of cases (Times of India, 2010; Amirapu, 2021). India's judicial system has a very high share of pretrial detainees in the world. Seventy percent of the total prisoner population in India is comprised of under-trial prisoners; the corresponding figures for the United States and Pakistan are 23% and 62%, respectively (Bharti and Roy, 2022).

In India, cases are also assigned to judges on an *as-good-as-random* basis Ash et al. (2022).[7] First, the complainant files a First Information Report (FIR) by reporting the crime to a local police station. Next, the case is assigned to a judge sitting in the courthouse in the territorial jurisdiction of the police station. In the case of multiple judges, the case is assigned to a particular courtroom, where a specific judge sits for a stint of several months. As judges rotate through different courtrooms during their tenure of two to three years at a given court, it is difficult to manipulate which judge handles a given case, conditional on police station and type of charge.[8]

4 Data

4.1 Judicial Data

Our data on judicial cases comes from the Indian eCourts platform, which is a partially-public data warehouse made available by the Indian government. It is comprised of approximately 77 million Indian court cases, both civil and criminal. We exploit the data made publicly available – case filings, registration, hearings, defendant characteristics and

[7]Ash et al. (2022) conduct balance tests to test the validity of the assumption of random case assignment to judges. They find that male and female defendants were equally likely to be assigned to female judges. In addition, Muslim and non-Muslim defendants were equally likely to be assigned to Muslim judges.

[8]Importantly, cases tend to "travel" with a given judge, so that if a case is still pending at the time a judge is transferred, that case will remain assigned to that same judge.

identifiers, decision date, and the final disposition or case outcome.

While the eCourts database covers all courts in India's lower judiciary, following Ash et al. (2022), we restrict the sample by focusing on non-bail-related court cases filed under the Indian Penal Code or the Code of Criminal Procedure. This sample restriction allows us to clearly distinguish between 'good' vs. 'bad' outcomes for criminal defendants, which can be more nebulous to identify in civil cases and bail-related cases in India.[9] We are interested in the impact of higher temperatures on judicial decision-making and thus, we exclude cases with dispositions such as confession, died, or plead guilty because they are not court outcomes in which the judge is the ultimate decision maker. Finally, having restricted the cases to those in which the judge is the final decision-maker, we define our outcome of interest as simply a binary indicator equal to 1 if the defendant is convicted and 0 if the defendant is acquitted for the offense by the judge. We focus on these two outcomes because they are the judicial decisions with the clearest positive or negative valence.[10] Our final estimation sample consists of 910,000 case records from 2010 to 2018.

Table 1 presents the summary statistics for our sample. We present summary statistics of various case characteristics in Panel B. In our sample, which is restricted to dispositions that are either convictions or acquittals, about 18% of the defendants in the sample are convicted (as opposed to acquitted).[11] As it relates to defendant and judge characteristics – 89% of defendants are men and 65% of judges are men. For type of criminal offenses in the sample: 55% of offenses are violent crimes, while 13% of the analysis sample are property crimes.[12]

[9] In addition, we restrict the sample to cases with consistent decision date and non-missing trial characteristics.

[10] In Subsection 6.2, we explore the robustness of our results to an alternate conviction measure that includes an expanded set of judicial decisions.

[11] The national conviction rate for India, when considering all possible dispositions is approximately 44%, according to the National Crime Records Bureau (`https://www.ceicdata.com/en/india/crime-statistics`). Our conviction rate is lower than the national average because we exclude convictions such as "plead guilty" or "confessed" that occurred due to a decision made by the defendant. We exclude these dispositions because we are interested in how temperatures affect *judicial* decision making. If we construct the conviction rate from the raw data and follow as closely as possible the national definition, we get a mean conviction rate of 43% — statistically similar to the national average for the analysis period.

[12] Of the remaining cases in our sample, 13% are crimes that we classified as neither property nor violent,

Table 1: Summary statistics

A: Weather Characteristics		
	Mean	S.D.
Daily max temperature in C (Temp)	29.870	4.917
Temp $\geq$ 33C	0.229	0.420
Temp $\geq$ 34C	0.173	0.378
Temp $\geq$ 35C	0.132	0.339
Temp $\geq$ 36C	0.103	0.303
Temp $\geq$ 37C	0.079	0.270
Temp $\geq$ 37.7C	0.064	0.245
Temp $\geq$ 38C	0.059	0.236
Temp $\geq$ 39C	0.041	0.199
Temp $\geq$ 40C	0.026	0.160
Daily max WBGT (in C)	24.195	3.929
WBGT $\geq$ 32C	0.014	0.117
Total daily precipitation (mm)	3.584	9.396
Mean daily PM2.5	71.386	57.146

B: Case Characteristics		
	Mean	S.D.
Conviction rate %	17.965	38.389
Female defendant	0.106	0.308
Male defendant	0.894	0.308
Trial duration	779.689	671.394
Female judge	0.322	0.467
Male judge	0.654	0.476
Violent crime	0.547	0.498
Property crime	0.128	0.335
Other crime	0.133	0.340
Missing crime type	0.192	0.394
N	910318	

Note: Our analysis sample consists of cases with either a conviction or an acquittal disposition (see Section 4 for more detail). All weather characteristics in Panel A are measured on the day of the conviction decision. In Panel B, the conviction rate is defined as the percent of these cases that are convictions.

4.2 Weather Data

We use reanalysis weather data from the ERA5 gridded dataset (Hersbach et al., 2020), which provides detailed information on temperature, precipitation, and relative humidity for the period 1979 to 2018. The ERA5 dataset provides weather information at a temporal resolution of 6-hour time steps, and at a spatial resolution of a 0.25 degree by 0.25 degree latitude-longitude grid.[13] To construct district-level weather outcomes from the gridded weather dataset, we take the inverse distance weighted average of all grid points that are within a 100-kilometer radius of a given district's geographic centroid. Since the data are given at 6-hour time steps, we construct the maximum temperature for a given day by taking the highest temperature value from the time steps that fall within that day. Because humidity is also known to affect heat stress on humans (Jing et al., 2013), we use the ERA5 data to construct wet bulb globe temperature (WBGT), a composite measure that factors in both temperature and relative humidity.[14] Similarly, to construct daily total precipitation for a given day, we take the sum of the precipitation values for each of the time steps that fall within that day.

and 19% are crimes that are missing penal section information. We use code provided by Ash et al. (2022) to extract and classify the crime types from the Section of Indian Penal Code Act or the Code of Criminal Procedure Act under which the case was filed. Violent crimes include suicide, homicide, dowry death, abatement of suicide, forced miscarriage and infanticide, injury, confinement, assault, kidnapping, trafficking and slavery, and sexual assault. Property crimes include theft, extortion, forgery, counterfeiting, cheating, and fraudulent deeds. Other crimes include abatement, criminal conspiracy, disturbed public health/tranquility, crimes against the state/army, and election crimes.

[13]We choose to use the ERA reanalysis dataset because high-resolution observational data on relative humidity is not available for India. For example, the Met Office's HadISDH gridded global surface humidity dataset (`https://www.metoffice.gov.uk/hadobs/hadisdh/`) is only available at a coarse temporal resolution (monthly) and also at a coarse spatial grid (5 degrees). On the other hand, high-resolution India-specific observational weather data from the Climate Research and Services at India Meteorological Department, Pune (`https://cdsp.imdpune.gov.in/`) lacks data on relative humidity. However, numerous previous economic studies have used the ERA reanalysis data in contexts that include India (Colmer, 2021; Heyes and Saberian, 2022; Colelli et al., 2023), the US (Hogan and Schlenker, 2023), Europe (Holtermann, 2020), and global analysis (Burke and Tanutama, 2019). Of these studies, several demonstrate that their results are robust to using either reanalysis or observational data, which is reassuring (Burke and Tanutama, 2019; Holtermann, 2020; Colmer, 2021; Hogan and Schlenker, 2023).

[14]Note that ERA5 does not provide direct information on relative humidity, but it gives information on dewpoint temperature. We use the dewpoint temperature to construct relative humidity using the formula from Lawrence (2005). We then use our measure of relative humidity to construct WBGT using the formula from Lemke and Kjellstrom (2012). This measure of WBGT is also used in the Indian context by Adhvaryu et al. (2020).

In addition to our weather data, we also integrate data on air pollution. We take advantage of EAC4 (ECMWF Atmospheric Composition Reanalysis 4) global reanalysis of atmospheric composition data that provides information on daily PM2.5 levels, with special resolution of 80 km, from 2003 to 2021.[15] Reanalysis combines PM2.5 measures from across the world with a model of the atmosphere based on the laws of physics to generate a complete and consistent dataset (Inness et al., 2019).

We present summary statistics of our weather measures in Table 1 Panel A. The average maximum daily temperature over the study period (2010-2018) is 29.9 °C, and 6.4% of the court decisions in our sample were made on days for which the maximum temperature exceeded 37.7 °C – the temperature threshold we use in our main regression analysis. We also consolidate maximum daily temperatures into bins with width 3°C. Figure 1 displays the fraction of cases in our sample that fall into each of our temperature bins. The modal temperature bin is the bin spanning temperatures from 27°C to 30°C, and about 4% of the cases occur on days in our highest bin (days for which the maximum temperature exceeded 39°C). Panels (a) and (b) of Appendix Figure A2 provide district-level maps of temperature and precipitation, respectively, for our sample.

5 Empirical Framework

To examine the relationship between maximum daily temperature and judicial outcomes in India, we adopt the following empirical specification:

$$Convicted_{ijkdmy} = \alpha + f(Temp_{kdmy}) + \pi W_{kdmy} + \theta X_i + \eta_j + \eta_k + \eta_m + \eta_y + \epsilon_{ijkdmy} \quad (1)$$

Subscript i denotes the defendant, j denotes the judge, k denotes the court district, and d, m, and y denotes case decision day, month, and year, respectively.[16] $Convicted_{ijkdmy}$ is

[15] `https://www.ecmwf.int/en/research/climate-reanalysis/cams-reanalysis`

[16] We make the key assumption that the temperature conditions leading to convictions would be most significant on the day the case decision is determined. In Appendix Table A6 we conduct a sensitivity check

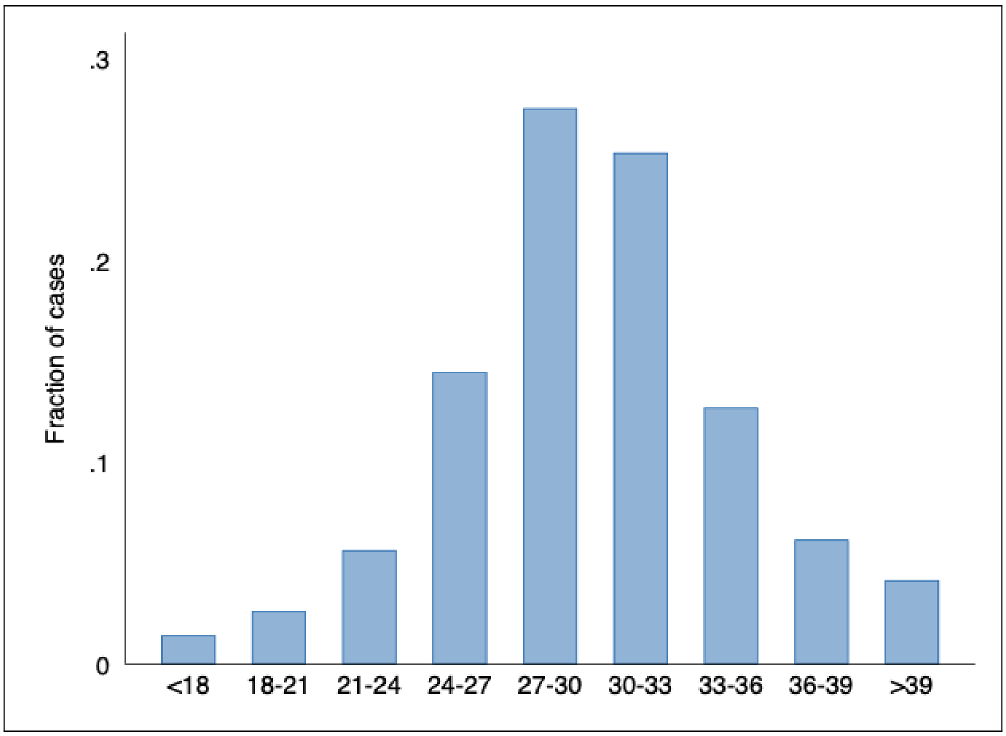


Figure 1: Distribution of Daily Maximum Temperature for Court Cases

Note: This figure plots the fraction of criminal court cases over maximum temperature bins in our sample.

a binary measure equals to 1 if the defendant was convicted of a crime and 0 if acquitted. The expression $f(Temp_{kdmy})$ is a function of daily maximum temperature in district k on the date of the final judicial decision. We run three separate specifications to capture the impact of temperature on decision-making: linear, threshold, and binned.

W_{kdmy} denotes controls for other relevant environmental factors, specifically total precipitation and average air pollution (PM2.5) on the decision date in district k. We include the control for air pollution because the literature confirms that exposure to pollution can influence cognition, mood, and decision-making (Archsmith et al., 2018; Chang et al., 2019; Ebenstein et al., 2016; Burkhardt et al., 2019). In some specifications, we control for trial characteristics – defendant gender, crime type, and trial duration – captured by the term X_i. The terms η_j, η_k, η_m and η_y capture judge fixed effects, district fixed effects, month fixed effects, and year fixed effects, respectively. The identifying assumption for our empirical analysis is that once we control for court, date, time, weather, and pollution controls, the remaining variation in maximum daily temperature is *as-good-as-random*, thus allowing for a causal interpretation of our regression coefficients. ϵ_{ijkdmy} is a spatially and serially correlated error term. Following the recommendations of Abadie et al. (2023), we cluster the standard errors at the district-month level to correspond directly with the level of the treatment assignment. Clustering at the district-month level allows for serial correlation.[17]

For the linear specification, we have simply:

$$f(Temp_{kdmy}) = \beta_{linear} Temp_{kdmy}$$

When we use this simple specification in equation 1, we are effectively assuming that there is a linear relationship between daily maximum temperature and conviction rates. However, the existing literature demonstrates the existence of important non-linearities in temperature effects, and this motivates our use of our next two specifications.

to test of this assumption by analyzing temperature over the entire trial period instead of just temperature on the date decision date. See Section 6 for further discussion.

[17] In Section 6.2, we verify that our results still hold if we use other levels of clustering.

Our second specification for temperature is a threshold specification of the form:

$$f(Temp_{kdmy}) = \beta_{threshold} I(Temp_{kdmy} \geq 37.7°C)$$

Here, our temperature specification is a binary indicator equal to 1 if the daily maximum temperature on the decision date exceeded 37.7°C, and 0 otherwise. This specification assumes that below a certain threshold, temperature effectively has no impact on conviction rates, but that above the threshold there is a discrete impact on conviction rates. We chose the value of $37.7C \approx 100F$ as the threshold, because earlier studies on extreme heat in India have either used this as a threshold (Heyes and Saberian, 2022) or found significant temperature impacts near this temperature level (Somanathan et al., 2021).

Finally, our third specification relies on temperature bins. Specifically, this binned specification takes the form:

$$f(Temp_{kdmy}) = \sum_{j=1}^{9} \beta_{bins,j} I(Temp_{kdmy} \in bin_j)$$

Each bin_j is of width of 3°C, with the bottom and top bins capturing temperature less than 18°C and more than 39°C, respectively.[18] We estimate separate coefficients for each of these nine bins and we omit the bin 21–24°C as our reference category to avoid perfect multicollinearity. For each of the remaining bins, the coefficient $\beta_{bins,j}$ captures the impact on conviction rates of a day in bin_j, relative to a day in the reference bin. Temperature binning is a flexible technique that allows the researcher to capture nonlinear impacts of temperature on various outcomes, and has already been used broadly in the economics literature (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011; Dell et al., 2014).

Across all three of these temperature specifications, we expect to find that higher maxi-

[18]Specifically, the set of bins we use are < 18, 18-21, 21-24, 24-27, 27-30, 30-33, 33-36, 36-39, and > 39. We chose this set of temperature bins based on the temperature distribution displayed on Figure 1.

mum daily temperature will lead to increased rates of convictions. In other words, we expect to find $\beta_{linear} > 0$ and $\beta_{threshold} > 0$, and, for our binned specification, we expect to find $\beta_{bins,j} > 0$ for large values of j.

6 Results

6.1 Main Results

In this section, we discuss the effects of daily maximum temperature on convictions, controlling for year, month, judge, and district fixed effects, along with trial characteristics – defendant gender, crime type, and trial duration. Columns (1) and (2) of Table 2 show that in general, rising daily maximum temperatures statistically significantly increase the probability of a conviction. Column (1) shows that the overall probability of a conviction increases by approximately 0.07 percentage points when temperature rises by 1°C. We find an estimate of 0.06 percentage points in column (2) once we add controls for trial characteristics to the model. Given that the standard deviation of maximum daily temperature in our sample is 4.917, our estimates demonstrate that a one standard deviation increase in temperature increases conviction rates by 0.335 percentage points, which represents a 1.9% increase relative to the baseline conviction rate of 17.96%. Although the size of this effect might appear small, it is important to note that using the linear model will significantly underestimate true impacts, if there important non-linearities in the temperature-conviction relationship.

Thus, to show the impact of extreme temperatures on conviction rates, we also explore the threshold specification, showing how temperatures above 37.7°C affect the likelihood of conviction. Columns (3) and (4) indicate that on days when the maximum temperature exceeds 37.7°C, the probability of a conviction increases by 1.13 and 1.11 percentage points, respectively, relative to days with the maximum temperature below 37.7°C. Relative to the baseline mean of our conviction rate variable, these estimates suggest that on days with

Table 2: The effect of daily maximum temperature on conviction rate

	Linear		Threshold		Binned	
	(1)	(2)	(3)	(4)	(5)	(6)
Temp	0.0681***	0.0633***				
	(0.0177)	(0.0173)				
Temp $\geq$ 37.7C			1.1341***	1.1070***		
			(0.2349)	(0.2326)		
<18					-1.2168**	-1.2659***
					(0.4843)	(0.4717)
18-21					-0.2770	-0.3044
					(0.3189)	(0.3124)
24-27					0.0725	0.0238
					(0.2498)	(0.2436)
27-30					0.2618	0.1807
					(0.2737)	(0.2659)
30-33					0.1829	0.1020
					(0.2785)	(0.2721)
33-36					0.3143	0.2290
					(0.3197)	(0.3120)
36-39					0.7511**	0.6041
					(0.3821)	(0.3725)
39+					1.5003***	1.4013***
					(0.4016)	(0.3944)
Outcome mean	17.96	17.96	17.96	17.96	17.96	17.96
Outcome SD	38.39	38.39	38.39	38.39	38.39	38.39
R-squared	0.26	0.27	0.26	0.27	0.26	0.27
N	910318	910318	910318	910318	910318	910318
Trial controls		X		X		X

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day. Trial controls include defendant gender, crime type, and trial duration. The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

maximum temperatures above 37.7°C the conviction probability increases by 6.2 % to 6.3%, compared to days when maximum temperature falls below this threshold.

In addition to estimating linear and threshold effects, we examine possible non-linear relationships in Columns (5) and (6) in Table 2; these results are also presented graphically in Figure 2. Evaluating the temperature-convictions relationship using the binned specification also reveals striking results. Table 2 shows that compared to temperatures in the 21–24°C range (our reference bin), temperatures above 36°C increase the likelihood of a conviction, holding all else constant. With no trial controls, the probability of receiving a conviction is 0.75 percentage points ($p < 0.05$) higher when maximum temperatures are in the 36-39°C range, compared to when the temperature is within the 21-24°C range. Moreover, the probability of receiving a conviction is 1.5 percentage points ($p < 0.01$) higher when temperatures are above 39°C. With trial controls, the probability of receiving a conviction is 1.4 percentage points ($p < 0.01$) higher when temperatures are above 39°C. When compared to the conviction mean, the evidence suggests that daily maximum temperatures within the 36-39°C range increase the likelihood of a conviction by about 4%, while temperatures above 39°C increase conviction rates by about 8%.

To verify that the specific threshold we have chosen for hot days (37.7°C) is not driving our results, in Figure 3, we present the results of several different regressions that employ different thresholds, varying from 33°C to 40°C. The point estimates of the coefficients of all these different thresholds are positive, and they are statistically significant at the 5% level for all thresholds 35°C or higher. The coefficient magnitudes are roughly the same for thresholds set anywhere from 37°C to 40°C. Thus, Figure 3 is reassuring and demonstrates that our results are not driven by the particular threshold we have chosen.

Across all three of our temperature specifications, we find that higher temperatures lead to an increase in the probability of a conviction. It is unlikely that these temperature-induced increases in judicial harshness are optimal given that recent literature shows that extreme heat impairs cognitive performance (Graff Zivin et al., 2018; Krebs, 2022; Park,

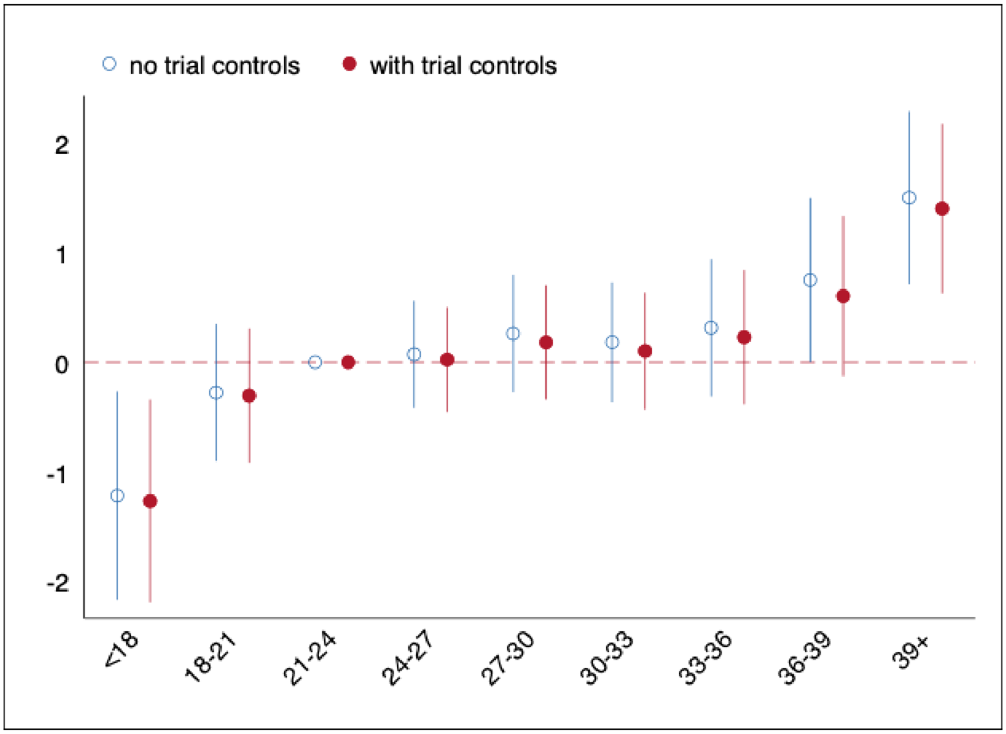


Figure 2: The effect of daily maximum temperature on conviction rate: nonlinear estimates

Note: This figure plots the coefficient estimates and their 95% confidence interval bands on the temperature indicator variables from estimation of the nonlinear specification. Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We also control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender, crime type, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

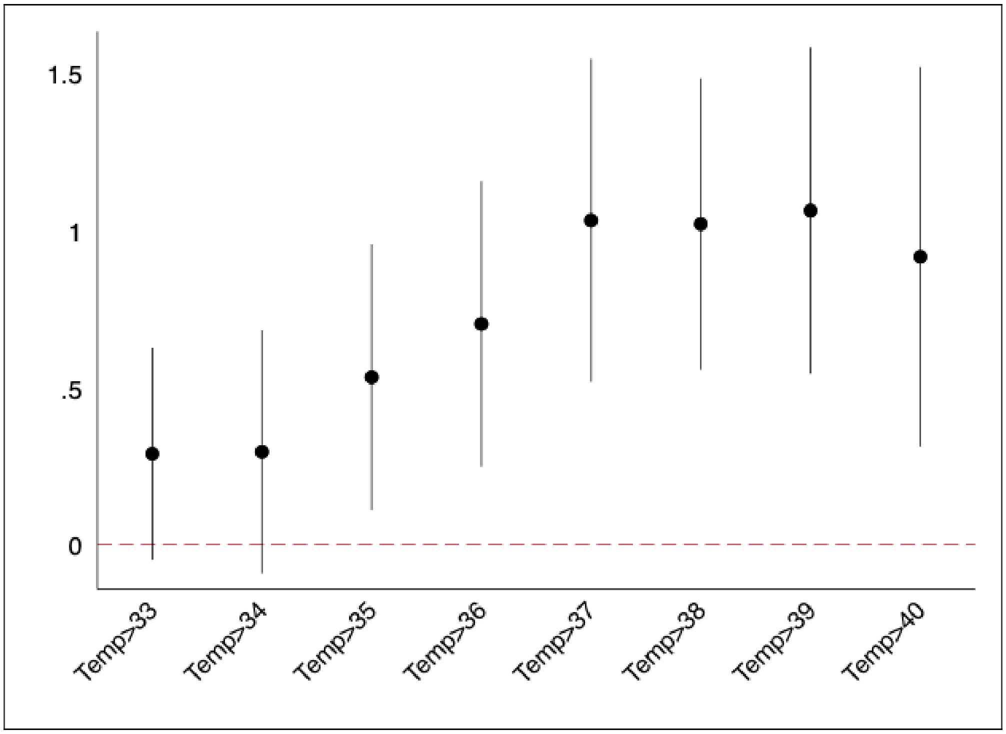


Figure 3: The effect of daily maximum temperature on conviction rate: different thresholds

Note: This figure plots the coefficient estimates of different threshold specifications and their 95% confidence interval bands. Each threshold is an indicator that equals to 1 if daily maximum temperature exceeds the temperature specified on the x-axis. The sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We also control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender, crime type, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

2022), reduces productivity (Behrer et al., 2021), increases impatience (Carias et al., 2021), and increases observable correlates of negative mood states, such as expressed sentiment (Baylis, 2020).

Table 3 shows the impact of all three temperature specifications on the probability of a conviction across three types of crime: violent, property, and other. Appendix Figure A3 presents graphically the estimates from the temperature bin specification. We find a positive and statistically significant effect of higher temperatures on conviction rates for violent crimes across all three of our temperature specifications (linear, threshold, and binned), which provides consistent evidence that high temperatures impact conviction rates for violent crimes. On the other hand, the evidence for property crimes and other crimes is more mixed: we find a statistically significant effect on property crime conviction rates only in the linear model; while for other crimes, we find a statistically significant effect only in the threshold model.

One concern regarding our estimates in both Tables 2 and 3 is whether these estimates might simply capture the impact of temperature extremes on criminal behavior. In reality, this explanation is unlikely because the Indian judicial system is characterized by lengthy case backlogs, strongly suggesting that the estimates on the likelihood of conviction do not serve as proxy estimates on crime.

Table 4 presents the impact of the gender of the judge on the probability of a conviction. The decision-making of female judges might be more susceptible to temperature extremes, since women are at a thermo-regulatory disadvantage under extreme heat stress, relative to men, (Cheung et al., 2000; Corbett et al., 2020) and, as a result heat stress may have a greater negative impact on cognition for women, relative to men, in certain contexts (Yi et al., 2021). Across all three of our temperature specifications, the point estimates of the impact of temperature on conviction rates are larger for female judges than male judges. However, the difference in the coefficients is not statistically significant in any of the three specifications.

Table 3: The effect of daily maximum temperature on conviction rate by crime type

	Linear			Threshold			Binned		
	Violent	Property	Other	Violent	Property	Other	Violent	Property	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Daily max temperature in C (Temp)	0.0788***	0.0899**	0.0514						
	(0.0206)	(0.0455)	(0.0465)						
Temp $\geq$ 37.7C				1.1984***	0.2464	1.5591**			
				(0.2803)	(0.6261)	(0.6646)			
<18							-0.8743	-2.3088*	-1.5475
							(0.5561)	(1.1783)	(1.4525)
18-21							-0.7725**	1.2612	0.3859
							(0.3721)	(0.8400)	(1.0875)
24-27							0.0553	0.4455	-0.0186
							(0.2906)	(0.6495)	(0.7940)
27-30							0.3207	1.1481*	0.0111
							(0.3128)	(0.6693)	(0.7662)
30-33							0.4240	1.2103*	-0.8877
							(0.3194)	(0.6983)	(0.8158)
33-36							0.6189*	0.9674	0.0511
							(0.3604)	(0.7965)	(0.9099)
36-39							0.6776	1.6242*	0.7780
							(0.4172)	(0.9478)	(1.1759)
39+							1.8467***	1.6791	1.1167
							(0.4697)	(1.0410)	(1.1413)
Observations	496486	113689	117585	496486	113689	117585	496486	113689	117585
R^2	0.226	0.354	0.542	0.226	0.354	0.542	0.227	0.354	0.542

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear, nonlinear, and threshold specifications by crime type. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

Table 4: The effect of daily maximum temperature on conviction rate by judge gender

	Linear		Threshold		Binned	
	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Daily max temperature in C (Temp)	0.0608***	0.0717**				
	(0.0213)	(0.0296)				
Temp $\geq$ 37.7C			0.9365***	1.7843***		
			(0.2937)	(0.4077)		
<18					-1.1870**	-1.4186*
					(0.5882)	(0.8199)
18-21					-0.6919*	0.6091
					(0.3750)	(0.5601)
24-27					0.1013	-0.0671
					(0.3008)	(0.4090)
27-30					0.1816	0.2429
					(0.3180)	(0.4642)
30-33					0.0490	0.2277
					(0.3315)	(0.4626)
33-36					0.3768	-0.0404
					(0.3811)	(0.5290)
36-39					0.3582	1.1949*
					(0.4475)	(0.6376)
39+					1.2998***	1.7633***
					(0.4872)	(0.6829)
Outcome mean	18.74	17.50	18.74	17.50	18.74	17.50
Outcome SD	39.02	38.00	39.02	38.00	39.02	38.00
R-squared	0.26	0.28	0.26	0.28	0.26	0.28
N	595614	282639	595614	282639	595614	282639

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear, nonlinear, and threshold specifications by defendant gender. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (crime type, defendant gender, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

We also explore the impact of temperature on the probability of conviction by the gender of the defendant, with the results presented in Appendix Table A1. The coefficients for the sample of male defendants are more precisely estimated than those of the female sample, but this is likely due to the fact that the sample of male defendants is about ten times larger than the sample of female defendants. The magnitudes of the coefficients for the male and female defendant samples are quite similar for our linear and threshold models; in the temperature bin model the point estimate of the male coefficient is larger, but not statistically significantly so. This absence of a statistically significant difference is sensible, given that we are focusing on an outcome from the judge, rather than from the defendant.

We next explore how our results vary based on the level of infrastructure in the court for a given court decision. We obtain data on litigant-friendly infrastructure from Chandrashekaran et al. (2021). The data come from the "Justice, Access and Lowering Delays in India" (JALDI) survey on the infrastructure of India district courts conducted in 2018. These data report an infrastructure index that measures the percent of infrastructure amenities beneficial to litigants (such as air conditioning in waiting rooms) within a district court complex.[19] We therefore explore the impact of temperature on the probability of conviction by whether the court has an infrastructure index above or below the median in our sample. The results of this analysis are presented in Table 5. We find that in courts with higher levels of infrastructure, the impact of temperature is smaller than our baseline estimates from Table 2 and is not statistically significant in the linear or temperature bin models. In contrast, for the courts with lower levels of infrastructure, the point estimates for the linear, threshold, and temperature bin models are larger than the baseline estimates from Table 2 and are statistically significant in all three specifications. For our entire sample (in Table 2), a day in our highest temperature bin (over 39°C) increases conviction rates by 8%, relative

[19]Unfortunately, the data are not longitudinal and do not contain information regarding the amenities available to judges. However, from conversations with experts who conducted the JALDI survey, we are told that there is a high positive correlation between the quality of infrastructure available to litigants and the quality of infrastructure available to judges. Put simply, district courts with poor amenities available to litigants also have poor amenities available to judges.

Table 5: The effect of daily maximum temperature on conviction rate: heterogeneous effects by court infrastructure

	Linear		Threshold		Binned	
	high	low	high	low	high	low
	(1)	(2)	(3)	(4)	(5)	(6)
Daily max temperature in C (Temp)	0.0236	0.1066***				
	(0.0246)	(0.0243)				
Temp $\geq$ 37.7C			0.8959**	1.2968***		
			(0.3615)	(0.3006)		
<18					-1.0611	-1.6636***
					(0.7039)	(0.5838)
18-21					-0.4368	-0.2359
					(0.4561)	(0.4266)
24-27					-0.2860	0.2904
					(0.3787)	(0.3148)
27-30					-0.3888	0.7326**
					(0.4032)	(0.3506)
30-33					-0.5018	0.6913*
					(0.4051)	(0.3678)
33-36					-0.3534	0.8142**
					(0.4765)	(0.4110)
36-39					0.0800	1.1620**
					(0.5939)	(0.4717)
39+					0.4687	2.3145***
					(0.5862)	(0.5288)
Outcome mean	19.50	16.55	19.50	16.55	19.50	16.55
Outcome SD	39.62	37.16	39.62	37.16	39.62	37.16
R-squared	0.26	0.27	0.26	0.27	0.26	0.27
N	436341	473977	436341	473977	436341	473977

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear, nonlinear, and threshold specifications by different court characteristics. We split the sample to court decisions with infrastructure index above (high) or below (low) the median in our sample. Court infrastructure data were obtained from Chandrashekaran et al. (2021). Infrastructure index ranges from 6 to 100 and measures the percent of beneficial to the litigants infrastructure amenities each court complex has. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (crime type, defendant gender, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

to baseline conviction rates, whereas Table 5 demonstrates that for courts with low levels of infrastructure, temperatures in this range increase conviction rates by 13%. Further, the coefficients for the low infrastructure sample are statistically different from those in the high infrastructure sample for the temperature bin model. Taken as a whole, these results suggest that low levels of court infrastructure may intensify the impact of high temperatures on conviction rates.

6.2 Robustness Checks

In this subsection, we explore the robustness of our results to several variations in our specification. First, we test the sensitivity of our results to different sets of fixed effects. Appendix Table A2 explores our linear and threshold models while Appendix Table A3 explores our binned model. The fixed effects that we include, in various combinations, are day-of-week, judge, district-month, judge-month, district, year, year-month, date, and month. Our estimates of the impact of high temperatures on conviction rates are largely consistent, positive, and statistically significant, across all three specifications, reinforcing the robustness of the main findings.

Second, we explore the sensitivity of our results to various levels of clustering of our standard errors. In our main specification, we cluster the standard errors at the district-month level, because this is the level of our treatment variable (weather), following Abadie et al. (2023). In Appendix Table A4, we explore the robustness of our linear and threshold estimates to district-level clustering and judge-level clustering, and in Appendix Figure A4 we do the same for our temperature bin estimates. Reassuringly, all our results are robust to these different levels of clustering.

Third, we test the robustness of our results to an alternate outcome measure. In our main results, we restrict the sample to decisions that are either convictions or acquittals, because these are the harshest and most lenient judicial decisions. In Appendix Table A5, we expand our sample to include a broader set of judicial outcomes: specifically, dispositions with outcomes of conviction, prison, fine, reject, acquitted, appeal, accepted, decided, disposed, judgment, probation, stayed, transferred, 258 crpc (acquittal), and referred to lok adalat. This selection of dispositions closely follows Ash et al. (2022), but we exclude dispositions for which the judge might not the primary decision-maker (e.g., plead guilty, withdrawn, and other). The dependent variable is a binary measure that equals one if the defendant case's disposition is conviction or prison, and 0 otherwise. The magnitude of our coefficients change since the mean of the dependent variable in the regression has changed, but, reassuringly, the signs and significance levels of the results are consistent with our main results.

Fourth, it is plausible that judges do not solely decide on case convictions on the documented decision date, but that the temperature on earlier hearing dates of the trial might also impact their decision-making process.[20] To explore this possibility, we evaluate the impact of the number of days over 37.7°C *during the entire trial period* on the likelihood of a conviction. Appendix Table A6 confirms that the impact of extreme temperatures over the course of the trial period is positive, statistically significant, and robust to a variety of fixed effects. The magnitude of the coefficient, however, is significantly smaller. This finding is not surprising given that temperatures over the course of the trial may influence the judge, but are unlikely to surpass temperature effects on the actual decision date.

Fifth, it is possible that relative humidity interacts with temperature in determining the level of heat stress on humans. To explore this possibility, we re-estimate our regressions using wet bulb globe temperature (WBGT) – a composite measure of heat stress that factors in both temperature and relative humidity. The results of this analysis, for our linear, threshold, and temperature bin models, are presented in Appendix Table A7, with the temperature bin analysis also presented graphically in Appendix Figure A5. We note that the WBGT measure has a compressed range compared to regular temperature (e.g., holding relative

[20] In addition to uncertainty about the timing of the judicial decision, it is unclear whether the decision is made in the court house, at the judge's home, or elsewhere. Furthermore, we do not have data on whether judges have air conditioning at home. However, earlier research demonstrates that even in the presence of cooling technologies, high outdoor temperatures can still affect decision-making (Yi et al., 2021; Zhang et al., 2021).

humidity constant, a 1°C change in WBGT corresponds to a greater than 1°C change in regular temperature) and so, to compensate for this, we adjust our threshold cut off and temperature bins accordingly. Reassuringly, our results are robust to using the WBGT measure. We note that the compressed range of the WBGT measure explains the smaller coefficient sizes in Appendix Table A7, compared to our baseline results. In addition, in Appendix Figure A6, we explore the sensitivity of our WBGT threshold results to using different thresholds, ranging from 25°C to 33°C, and we find statistically significant impacts for the thresholds of 31°C, 32°C, and 33°C.

Sixth, since the climate of India varies across its different regions, it is possible that the impact of high temperatures has differential effects in different regions of India. We explore this possibility in Appendix Figure A7. This figure disaggregates India into its six regions and then explores the impact of hot days (at temperature thresholds varying from 33°C to 40°C) on conviction rates.[21] For most regions, the point estimates for the impact of temperature on conviction rates increase as temperatures rise. For the Northeastern region, we find very flat estimates of the impact of temperature on conviction rates, but this is likely because this region has very few days in the top three temperature bins (see Appendix Figure A8), which are typically the bins for which we estimate the largest impacts. Across all six regions, the estimates using this approach are quite noisily estimated, likely due to the smaller sample size. Therefore, we are unable to draw any clear conclusions from this analysis.

Finally, in Appendix Table A8, we explore whether the impact of high temperatures on conviction rates varies depending on the level of air pollution on the day of the court decision. As seen in the table, the point estimates for the impact of temperature are slightly higher for the low pollution days than for the high pollution days, which is slightly counterintuitive. However, it is important to note that the coefficients across the two groups are not statistically significantly different, and thus we cannot draw inferences based on the magnitude of

[21] Appendix Figure A8 displays the distribution of temperatures for each region.

the coefficients. One reason we may be failing to detect a statistically significant difference between the two samples is that our air pollution measure is measured at the month level, which is not very temporally granular.

7 Conclusion

A burgeoning literature explores the role of rising temperatures in everyday decision-making. We add to this literature by showing how daily maximum temperatures affect the probability of criminal convictions in India. We exploit data from the Indian eCourt platform (2010–2018) merged with high-resolution temperature data to evaluate this research problem. Using three different specifications, we find that rising temperatures have a positive and statistically significant impact on the likelihood of conviction, and that these effects appear to be highly non-linear. Overall, our results document that conviction rates are higher on hotter days. We also uncover that temperature-driven convictions are especially significant for violent crimes and that impacts are larger in courts with lower quality infrastructure. We cannot directly test whether these heat-induced increases in judicial harshness are sub-optimal. But, it seems unlikely that these increases are optimal given that existing research has shown extreme heat leads to reductions in cognitive performance (Graff Zivin et al., 2018; Krebs, 2022; Park, 2022), economic productivity (Behrer et al., 2021), patience (Carias et al., 2021), and positive mood states (Baylis, 2020).

The existing literature on judicial outcomes and temperature focuses on high-income countries (United States, Australia) and, furthermore finds mixed results. Some studies find that high temperatures increase judicial harshness (Heyes and Saberian, 2019; Behrer and Bolotnyy, 2022), while others fail to detect such an effect (Siminski and Evans, 2021; Spamann, 2022). We contribute to this literature by exploring the impact of temperature on judicial outcomes on a middle-income country that experiences a high level of baseline heat. Our findings may, as a result, be applicable to other low- or middle- income countries that face a similar heat burden. We also contribute to a broader climate-economy literature that finds that the adverse impacts of higher temperatures are often intensified in low- and middle-income countries, relative to high-income countries (Dell et al., 2012; Burgess et al., 2017; Diffenbaugh and Burke, 2019).

Our results suggest a few promising avenues for future research. First, future research could undertake a similar research design, but for other low- or middle-income countries for which the temperature–conviction relationship has not yet been studied. Second, future research might gather court-level data on access to cooling technologies, and explore whether such access mitigates the effects that we find. Third, while our study focuses on judicial harshness, another important outcome to explore is judicial productivity, especially since the backlog of cases (pedancy) in India is currently a point of critical concern. Future research could explore whether higher temperatures reduce judicial productivity, leading to fewer cases cleared on days that are especially hot. Such research may also shed valuable insight into a potential cause of the backlog that India's courts face today.

Competing Interests

The authors declare no competing interests.

References

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2023): "When should you adjust standard errors for clustering?" *The Quarterly Journal of Economics*, 138, 1–35.

Adhvaryu, A., N. Kala, and A. Nyshadham (2020): "The light and the heat: Productivity co-benefits of energy-saving technology," *Review of Economics and Statistics*, 102, 779–792.

Allen, M. A. and G. J. Fischer (1978): "Ambient temperature effects on paired associate learning," *Ergonomics*, 21, 95–101.

Almås, I., M. Auffhammer, T. Bold, I. Bolliger, A. Dembo, S. M. Hsiang, S. Kitamura, E. Miguel, and R. Pickmans (2019): "Destructive behavior, judgment, and economic decision-making under thermal stress," Tech. rep., National Bureau of Economic Research.

Amirapu, A. (2021): "Justice delayed is growth denied: The effect of slow courts on relationship-specific industries in India," *Economic Development and Cultural Change*, 70, 415–451.

Anderson, C. A., W. E. Deuser, and K. M. DeNeve (1995): "Hot temperatures, hostile affect, hostile cognition, and arousal: Tests of a general model of affective aggression," *Personality and social psychology bulletin*, 21, 434–448.

Annan-Phan, S. and B. A. Ba (2020): "Hot temperatures, aggression, and death at the hands of the police: Evidence from the US," Retrieved from `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3356045`.

Archsmith, J., A. Heyes, and S. Saberian (2018): "Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation," *Journal of the Association of Environmental and Resource Economists*, 5, 827–863.

Ash, E., S. Asher, A. Bhowmick, S. Bhupatiraju, D. Chen, T. Devi, C. Goessmann, P. Novosad, and B. Siddiqi (2022): "In-group bias in the Indian judiciary: Evidence from 5 million criminal cases," Retrieved from `https://www.devdatalab.org/judicial-bias`.

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

Behrer, A., R. Park, G. Wagner, C. Golja, and D. Keith (2021): "Heat has larger impacts on labor in poorer areas," *Environmental Research Communications*, 3, 095001.

Behrer, A. P. and V. Bolotnyy (2022): "Heat, Crime, and Punishment," World Bank Policy Research Working Paper. Retrieved from https://openknowledge.worldbank.org/handle/10986/36881.

Bharti, N. K. and S. Roy (2022): "The early origins of judicial stringency in bail decisions: Evidence from early-childhood exposure to Hindu-Muslim riots in India," Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4078646.

Burgess, R., O. Deschenes, D. Donaldson, and M. Greenstone (2017): "Weather, climate change and death in India," *University of Chicago*.

Burke, M. and V. Tanutama (2019): "Climatic constraints on aggregate economic output," Retrieved from https://www.nber.org/system/files/working_papers/w25779/w25779.pdf.

Burkhardt, J., J. Bayham, A. Wilson, E. Carter, J. D. Berman, K. O'Dell, B. Ford, E. V. Fischer, and J. R. Pierce (2019): "The effect of pollution on crime: Evidence from data on particulate matter and ozone," *Journal of Environmental Economics and Management*, 98, 102267.

Carias, M. E., D. Johnston, R. Knott, and R. Sweeney (2021): "The Effects of Temperature on Economic Preferences," ArXiv preprint. Retrieved from https://doi.org/10.48550/arXiv.2110.05611.

Chandrashekaran, S., D. Sanyal, and R. Sekhar (2021): "Building Better Courts Surveying the Infrastructure of India's District Courts," Retrieved from https://vidhilegalpolicy.in/wp-content/uploads/2019/08/National-report_BBC.pdf.

Chang, T. Y., J. Graff Zivin, T. Gross, and M. Neidell (2019): "The effect of pollution on worker productivity: Evidence from call center workers in China," *American Economic Journal: Applied Economics*, 11, 151–72.

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

Chen, D. L., T. J. Moskowitz, and K. Shue (2016): "Decision making under the gambler's fallacy: Evidence from asylum judges, loan officers, and baseball umpires," *The Quarterly Journal of Economics*, 131, 1181–1242.

Cheung, S. S., T. M. McLellan, and S. Tenaglia (2000): "The thermophysiology of uncompensable heat stress," *Sports Medicine*, 29, 329–359.

Colelli, F. P., I. S. Wing, and E. D. Cian (2023): "Air-conditioning adoption and electricity demand highlight climate change mitigation–adaptation tradeoffs," *Scientific Reports*, 13, 4413.

Colmer, J. (2021): "Temperature, labor reallocation, and industrial production: Evidence from India," *American Economic Journal: Applied Economics*, 13, 101–124.

Corbett, J., J. Wright, and M. J. Tipton (2020): "Sex differences in response to exercise heat stress in the context of the military environment," *BMJ Mil Health*.

Cunningham, M. R. (1979): "Weather, mood, and helping behavior: Quasi experiments with the sunshine samaritan." *Journal of personality and social psychology*, 37, 1947.

Danziger, S., J. Levav, and L. Avnaim-Pesso (2011): "Extraneous factors in judicial decisions," *Proceedings of the National Academy of Sciences*, 108, 6889–6892.

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

——— (2014): "What do we learn from the weather? The new climate-economy literature," *Journal of Economic Literature*, 52, 740–98.

Denissen, J. J., L. Butalid, L. Penke, and M. A. Van Aken (2008): "The effects of weather on daily mood: A multilevel approach." *Emotion*, 8, 662.

Deschênes, O. and M. Greenstone (2007): "The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather," *American Economic Review*, 97, 354–385.

——— (2011): "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US," *American Economic Journal: Applied Economics*, 3, 152–85.

Diffenbaugh, N. S. and M. Burke (2019): "Global warming has increased global economic inequality," *Proceedings of the National Academy of Sciences*, 7, 201816020–6.

Ebenstein, A., V. Lavy, and S. Roth (2016): "The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution," *American Economic Journal: Applied Economics*, 8, 36–65.

Englich, B. and K. Soder (2009): "Moody experts—How mood and expertise influence judgmental anchoring," *Judgment and Decision making*, 4, 41.

Eren, O. and N. Mocan (2018): "Emotional judges and unlucky juveniles," *American Economic Journal: Applied Economics*, 10, 171–205.

Garg, T., M. Jagnani, and V. Taraz (2020): "Temperature and human capital in India," *Journal of the Association of Environmental and Resource Economists*, 7, 1113–1150.

Graff Zivin, J., S. M. Hsiang, and M. Neidell (2018): "Temperature and human capital in the short and long run," *Journal of the Association of Environmental and Resource Economists*, 5, 77–105.

Guthrie, C., J. J. Rachlinski, and A. J. Wistrich (2007): "Blinking on the bench: How judges decide cases," *Cornell L. Rev.*, 93, 1.

Hancock, P. A. and I. Vasmatzidis (2003): "Effects of heat stress on cognitive performance: The current state of knowledge," *International Journal of Hyperthermia*, 19, 355–372.

Harrington, L. J., D. J. Frame, E. M. Fischer, E. Hawkins, M. Joshi, and C. D. Jones (2016): "Poorest countries experience earlier anthropogenic emergence of daily temperature extremes," *Environmental Research Letters*, 11, 055007.

Harris, A. P. and M. Sen (2022): "How Judges' professional experience impacts case outcomes: An examination of public defenders and criminal sentencing," .

Hersbach, H., B. Bell, P. Berrisford, S. Hirahara, A. Horányi, J. Muñoz-Sabater, ..., and J.-N. Thepaut (2020): "The ERA5 global reanalysis," *Quarterly Journal of the Royal Meteorological Society*, 146, 1999–2049.

Heyes, A. and S. Saberian (2019): "Temperature and decisions: Evidence from 207,000 court cases," *American Economic Journal: Applied Economics*, 11, 238–65.

——— (2022): "Hot days, the ability to work and climate resilience: Evidence from a representative sample of 42,152 Indian households," *Journal of Development Economics*, 155, 102786.

Hogan, D. and W. Schlenker (2023): "ERA5-Land and GMFD Uncover The Effect of Daily Temperature Extremes On US Agricultural Yields," Retrieved from https://ceep.columbia.edu/sites/default/files/content/papers/n25.pdf.

Holtermann, L. (2020): "Precipitation anomalies, economic production, and the role of "first-nature" and "second-nature" geographies: a disaggregated analysis in high-income countries," *Global Environmental Change*, 65, 102167.

Inness, A., M. Ades, A. Agustí-Panareda, J. Barré, A. Benedictow, A.-M. Blechschmidt, J. J. Dominguez, R. Engelen, H. Eskes, J. Flemming, et al. (2019): "The CAMS reanalysis of atmospheric composition," *Atmospheric Chemistry and Physics*, 19, 3515–3556.

Jaffe, J. (2017): "After Nanavati: The last jury trial in India?" *Economic & Political Weekly*, 52, 19.

Jing, S., B. Li, M. Tan, and H. Liu (2013): "Impact of relative humidity on thermal comfort in a warm environment," *Indoor and Built Environment*, 22, 598–607.

Johnston, D. W., R. Knott, S. Mendolia, and P. Siminski (2021): "Upside-down Down-Under: Cold temperatures reduce learning in Australia," *Economics of Education Review*, 85, 102172.

Krebs, B. (2022): "Temperature and Cognitive Performance," *Unpublished manuscript.*

Lawrence, M. G. (2005): "The Relationship between Relative Humidity and the Dew-point Temperature in Moist Air: A Simple Conversion and Applications," *Bulletin of the American Meteorological Society*, 86, 225–234.

Lemke, B. and T. Kjellstrom (2012): "Calculating workplace WBGT from meteorological data: a tool for climate change assessment," *Industrial Health*, 50, 267–278.

Ludwig, J. and S. Mullainathan (2021): "Fragile Algorithms and Fallible Decision-Makers: Lessons from the Justice System," *Journal of Economic Perspectives*, 35, 71–96.

Mendelsohn, R., A. Dinar, and L. Williams (2006): "The distributional impact of climate change on rich and poor countries," *Environment and development economics*, 11, 159–178.

Mukherjee, A. and N. J. Sanders (2021): "The causal effect of heat on violence: Social implications of unmitigated heat among the incarcerated," National Bureau of Economic Research Working Paper. Retrieved from `https://www.nber.org/system/files/working_papers/w28987/w28987.pdf`.

Obradovich, N., D. Tingley, and I. Rahwan (2018): "Effects of environmental stressors on daily governance," *Proceedings of the National Academy of Sciences*, 115, 8710–8715.

Park, R. J. (2022): "Hot Temperature and High-Stakes Performance," *Journal of Human Resources*, 57, 400–434.

Philippe, A. and A. Ouss (2018): ""No hatred or malice, fear or affection": Media and sentencing," *Journal of Political Economy*, 126, 2134–2178.

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

Rehdanz, K. and D. Maddison (2005): "Climate and happiness," *Ecological Economics*, 52, 111–125.

Schlenker, W. and M. J. Roberts (2009): "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of Sciences*, 106, 15594–15598.

Shumway, C. and R. Wilson (2022): "Workplace disruptions, judge caseloads, and judge decisions: Evidence from SSA judicial corps retirements," *Journal of Public Economics*, 205, 104573.

Siminski, P. and S. Evans (2021): "The Effect of Outside Temperatures on Criminal Court Sentencing Decisions," *Series of Unsurprising Results in Economics.*

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021): "The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing," *Journal of Political Economy*, 129, 1797–1827.

Spamann, H. (2022): "Comment on" Temperature and Decisions: Evidence from 207,000 Court Cases"," *American Economic Journal: Applied Economics*, 14, 519–28.

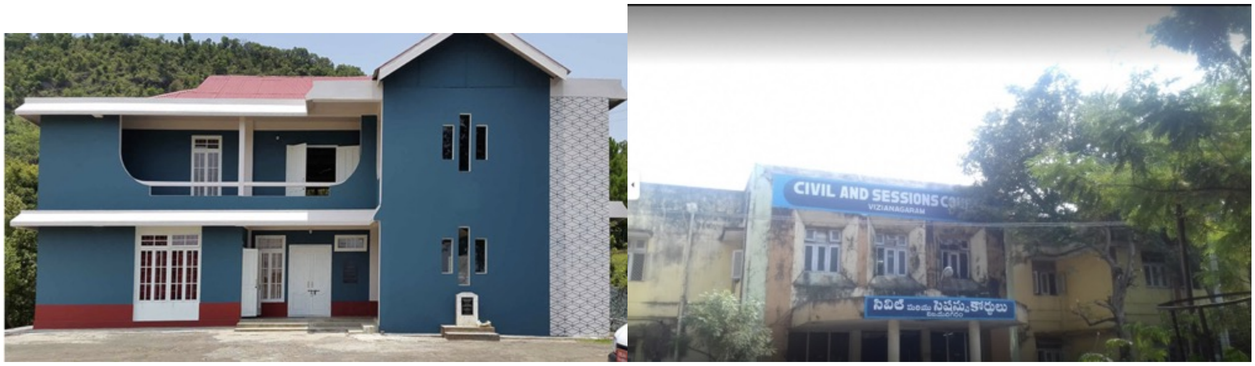
Stocker, T. F., D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, B. Bex, and B. Midgley (2013): *IPCC, 2013: Climate change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press.

Times of India (2010): "Courts will take 320 years to clear backlog cases: Justice Rao," *Times of India.*

Yi, F., T. Zhou, L. Yu, B. McCarl, Y. Wang, F. Jiang, and Y. Wang (2021): "Outdoor heat stress and cognition: Effects on those over 40 years old in China," *Weather and Climate Extremes*, 32, 100308.

Zhang, X., X. Chen, and X. Zhang (2021): "Temperature and Low-stakes Cognitive Performance," *medRxiv*, 2021–10.

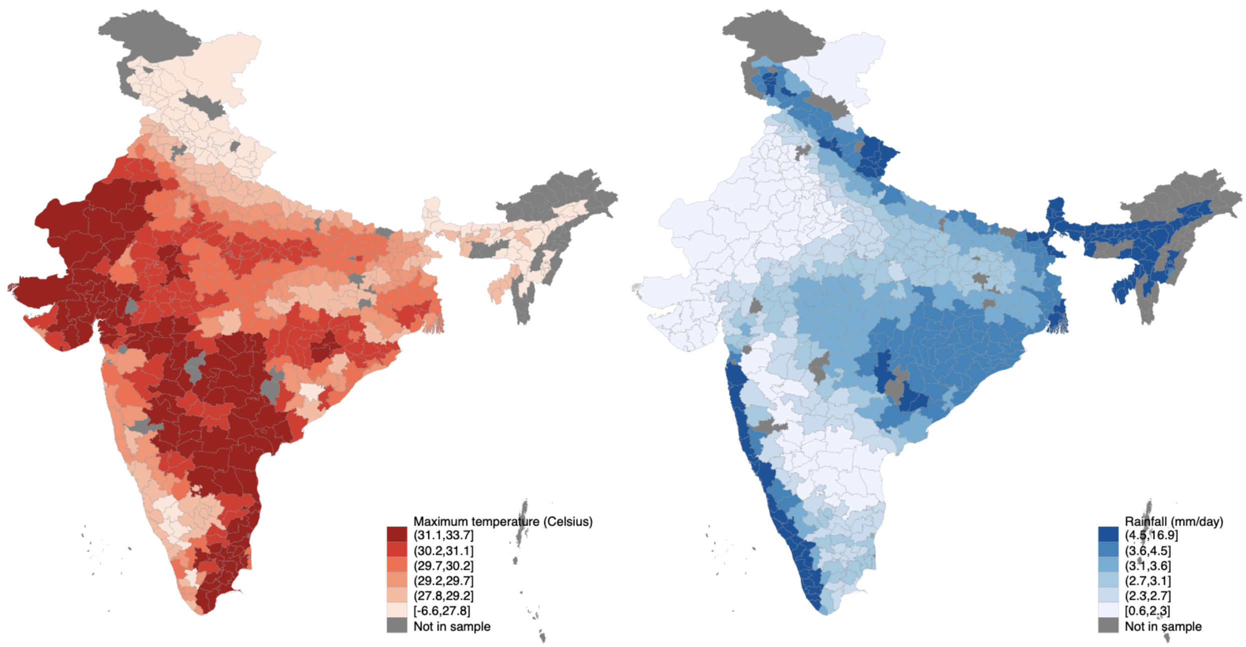
A Appendix: Supplementary Figures



(a) Champhai, Mizoram (b) Vizianagaram, Andhra Pradesh

Figure A1: Example of Indian district courts.

Note: Photos of district court complexes in India were obtained from `https://districts.ecourts.gov.in/`



(a) Annual average maximum temperature

(b) Annual total precipitation

Figure A2: Maps of maximum temperature and total precipitation.

Note: Annual average maximum daily temperature and annual total precipitation for India (2010-2018).

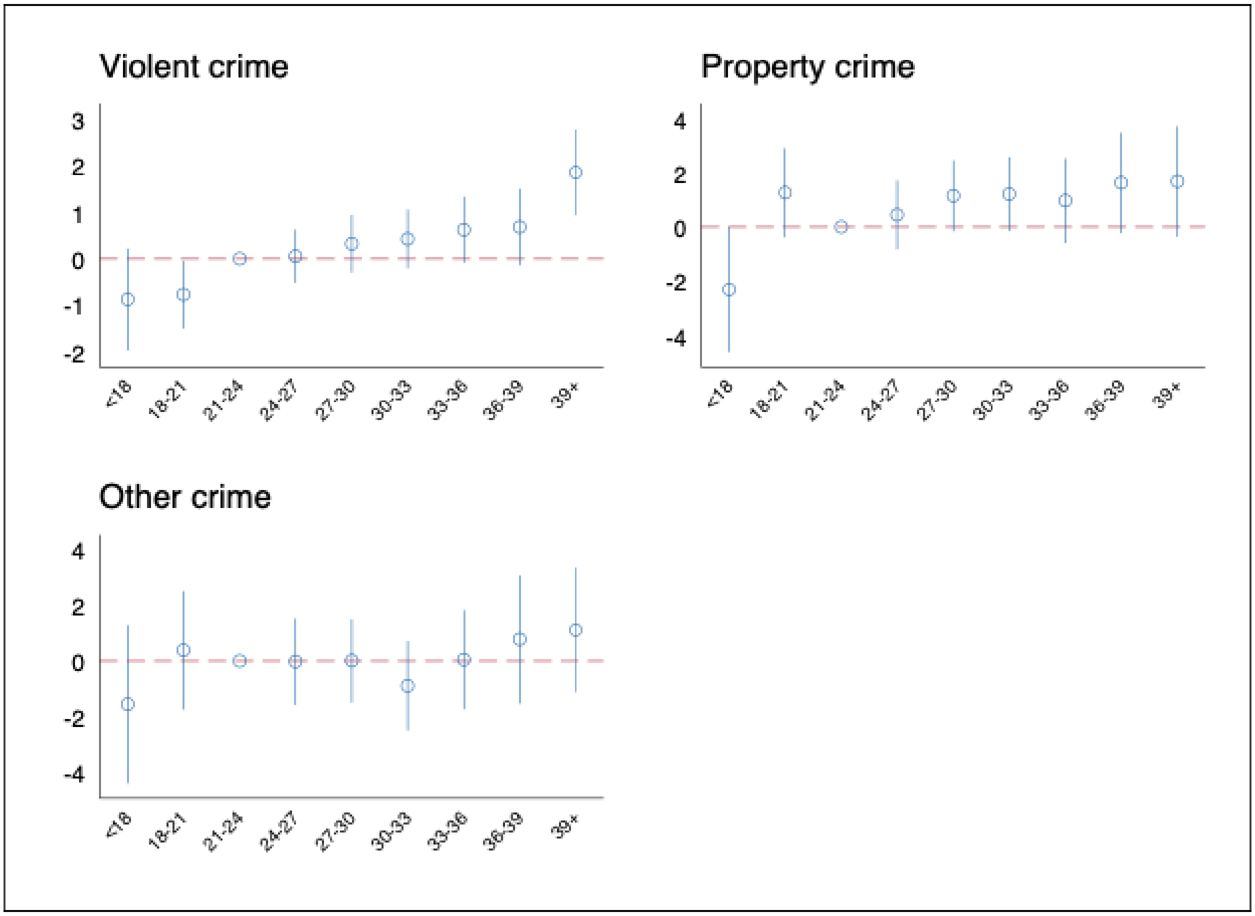


Figure A3: Nonlinear estimates by crime type

Note: This figure plots the coefficient estimates and their 95% confidence interval bands on the temperature indicator variables from estimation of the nonlinear specification by crime type. We also control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

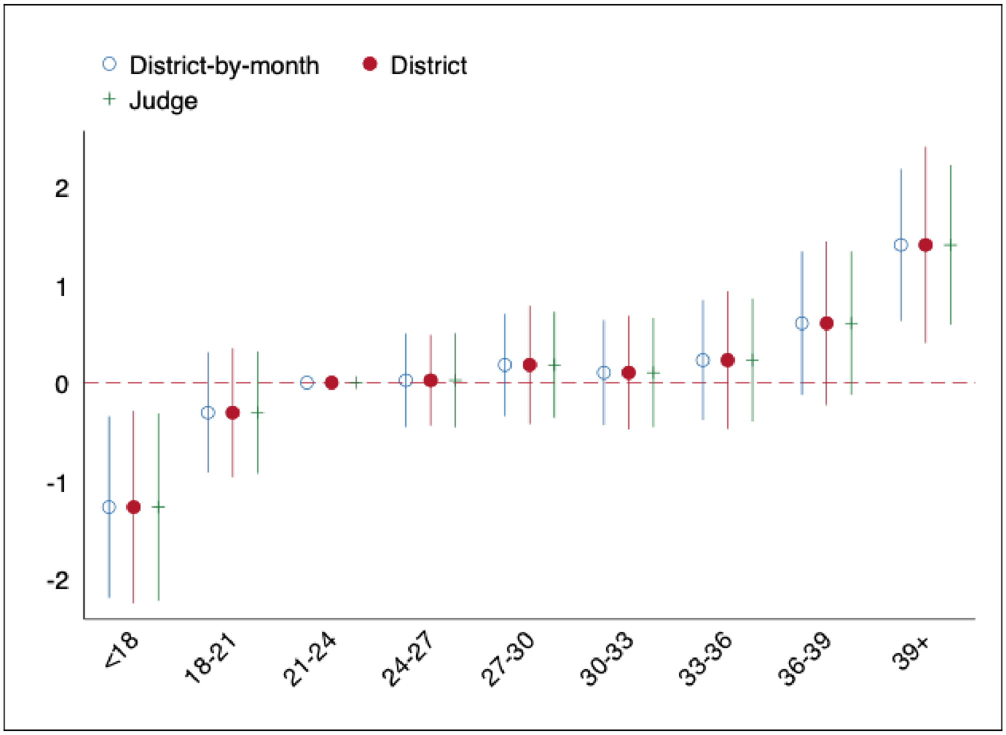


Figure A4: The effect of daily maximum temperature on conviction rate: nonlinear estimates robustness to clustering

Note: This figure plots the coefficient estimates and their 95% confidence interval bands on the temperature indicator variables from estimation of the nonlinear specification. We show the robustness of these estimates to different ways of clustering the standard errors. We also control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender, crime type, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

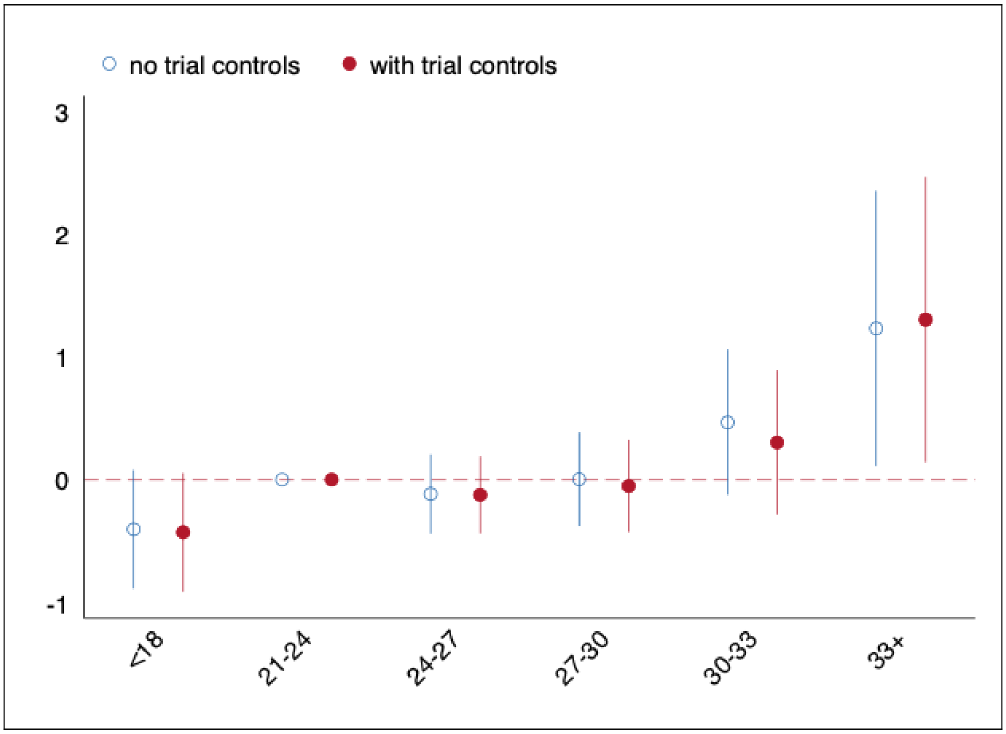


Figure A5: The effect of daily maximum WBGT on conviction rate: nonlinear estimates

Note: This figure plots the coefficient estimates and their 95% confidence interval bands on the temperature indicator variables from estimation of the nonlinear specification. The temperature is wet bulb globe temperature (WBGT), which is constructed using the formula from Lemke and Kjellstrom (2012). Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We also control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender, crime type, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

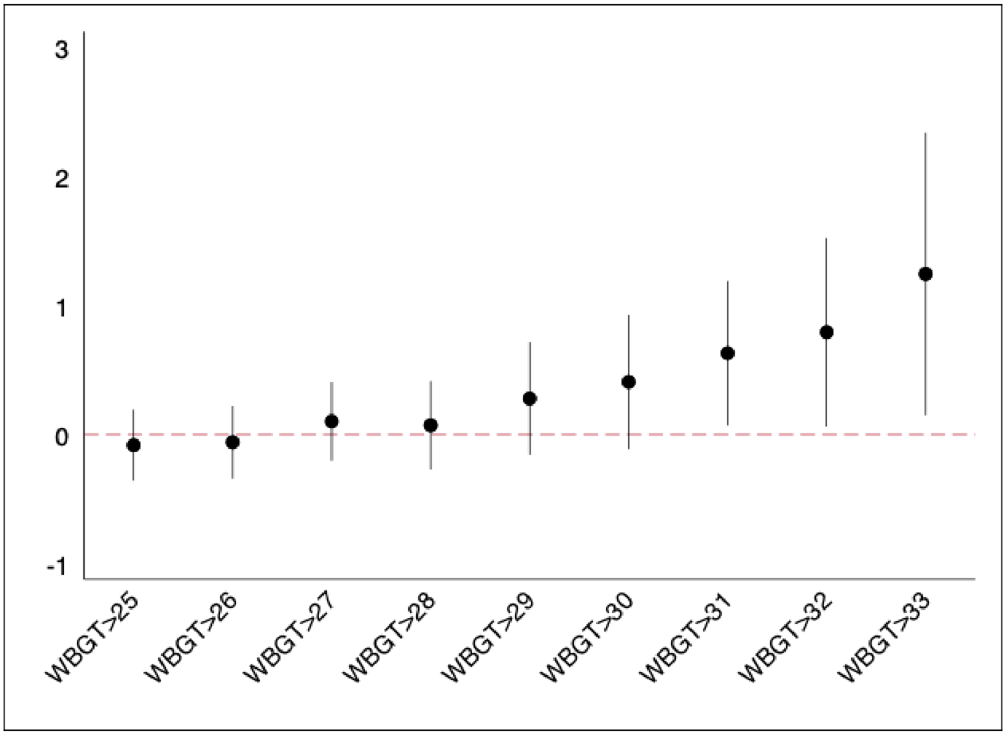


Figure A6: The effect of daily maximum WBGT on conviction rate: different thresholds

Note: This figure plots the coefficient estimates of different threshold specifications and their 95% confidence interval bands. Each threshold is an indicator that equals to 1 if daily maximum WBGT exceeds the temperature specified on the x-axis. Wet bulb globe temperature (WBGT) is constructed using the formula from Lemke and Kjellstrom (2012). Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We also control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender, crime type, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

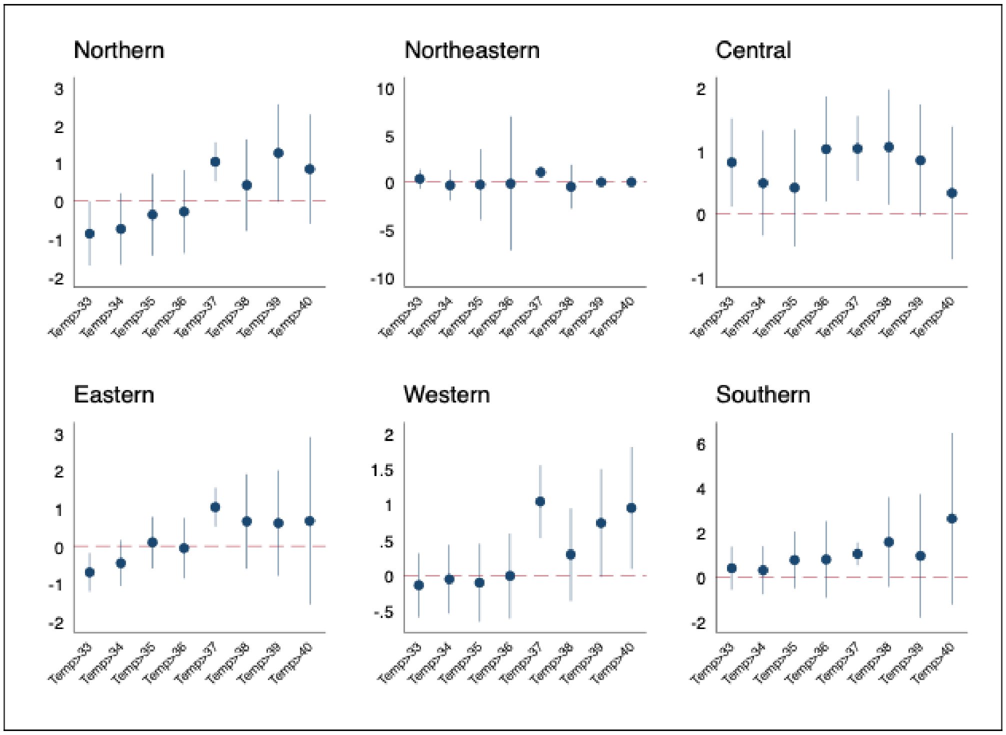


Figure A7: The effect of daily maximum temperature on conviction rate: different thresholds by region

Note: This figure plots the coefficient estimates of different threshold specifications and their 95% confidence interval bands by region. Each threshold is an indicator that equals to 1 if daily maximum temperature exceeds the temperature specified on the x-axis. Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We also control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (defendant gender, crime type, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

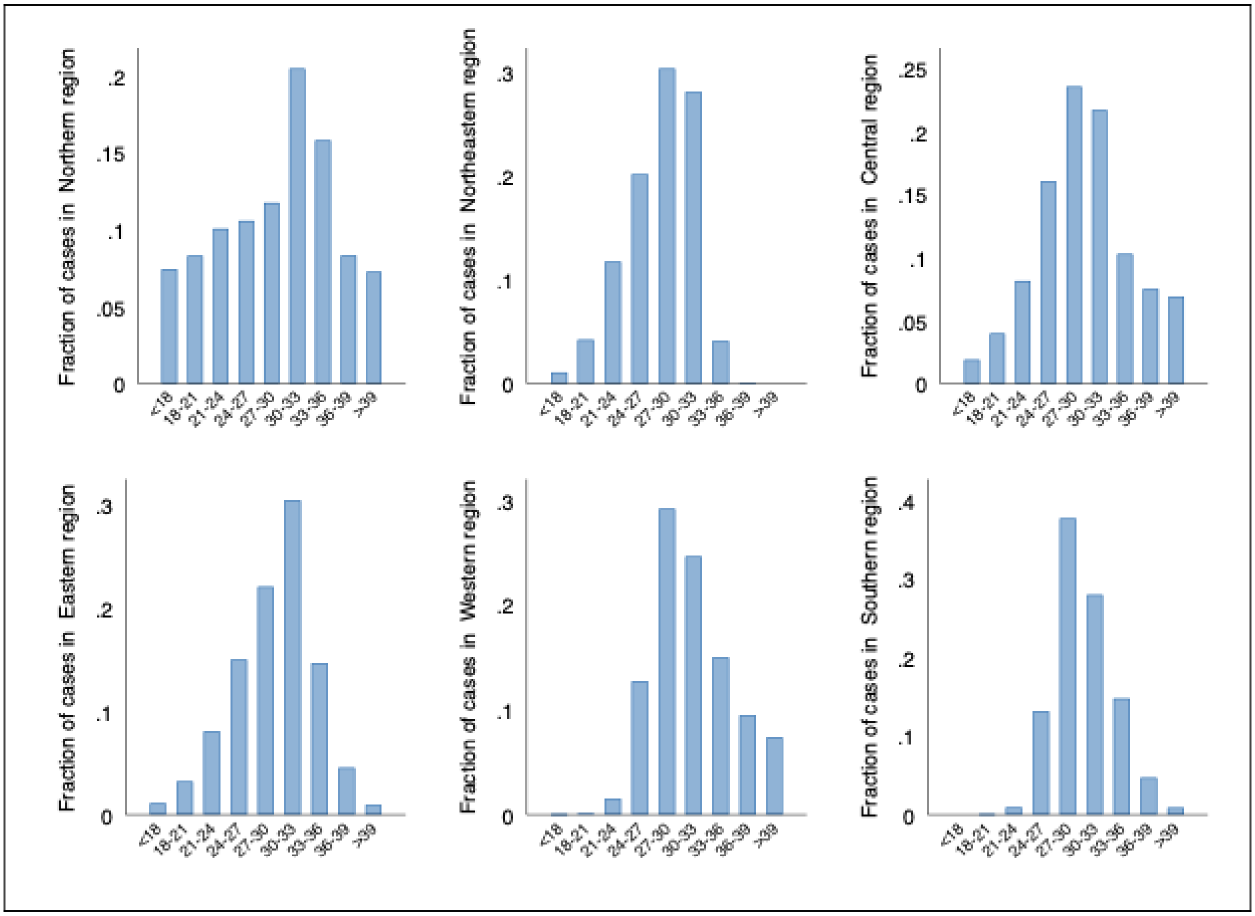


Figure A8: Distribution of Daily Maximum Temperature for Court Cases by Region

Note: This figure plots the fraction of criminal court cases over maximum temperature bins by region.

Appendix: Supplementary Tables

Table A1: The effect of daily maximum temperature on conviction rate by defendant gender

	Linear		Threshold		Binned	
	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Daily max temperature in C (Temp)	0.0635***	0.0709				
	(0.0176)	(0.0532)				
Temp $\geq$ 37.7C			1.1159***	1.2093		
			(0.2367)	(0.7466)		
<18					-1.1779**	-3.8955**
					(0.4816)	(1.6991)
18-21					-0.2679	-0.4870
					(0.3274)	(1.1327)
24-27					0.0282	-0.0655
					(0.2495)	(0.7255)
27-30					0.1387	0.4321
					(0.2707)	(0.7332)
30-33					0.1300	-0.4153
					(0.2771)	(0.7904)
33-36					0.1870	0.7680
					(0.3175)	(0.8997)
36-39					0.5671	0.8785
					(0.3808)	(1.0643)
39+					1.4337***	0.8846
					(0.4026)	(1.2516)
Outcome mean	17.93	18.37	17.93	18.37	17.93	18.37
Outcome SD	38.36	38.73	38.36	38.73	38.36	38.73
R-squared	0.27	0.33	0.27	0.33	0.27	0.33
N	813282	92855	813282	92855	813282	92855

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear, nonlinear, and threshold specifications by defendant gender. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (crime type and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Fixed Effects Sensitivity Analysis: Linear and threshold specification

	Linear Specification						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Daily max temperature in C (Temp)	0.0053	0.0987***	0.1037***	0.0474*	0.0533*	0.0533**	0.0633***
	(0.0122)	(0.0281)	(0.0244)	(0.0242)	(0.0279)	(0.0218)	(0.0173)
Outcome mean	17.96	17.97	17.97	17.97	17.96	17.97	17.96
Outcome SD	38.39	38.40	38.40	38.39	38.39	38.39	38.39
R-squared	0.27	0.16	0.15	0.38	0.29	0.28	0.27
N	910318	912360	912449	882489	910068	910231	910318
	Threshold specification						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temp $\geq$ 37.7C	0.7490***	0.7624*	1.1714***	0.8877***	0.9848***	0.7787***	1.1070***
	(0.2002)	(0.3990)	(0.3730)	(0.3007)	(0.2958)	(0.2694)	(0.2326)
Outcome mean	17.96	17.97	17.97	17.97	17.96	17.97	17.96
Outcome SD	38.39	38.40	38.40	38.39	38.39	38.39	38.39
R-squared	0.27	0.16	0.15	0.38	0.29	0.28	0.27
N	910318	912360	912449	882489	910068	910231	910318
Trial controls	X	X	X	X	X	X	X
Day of week FE	X	X	X	X		X	
Judge FE	X	X	X		X	X	X
District-month FE		X			X	X	
Judge-month FE				X			
District FE			X	X			
Year FE				X	X	X	X
Year-month FE			X				
Date FE					X		
Month FE					X		X

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear and threshold specifications. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day. Trial controls include crime type, defendant gender, and trial duration. Each specification contains various other fixed effects as indicated. Note that Column (9) is our main specification in Table 2. Standard errors are clustered at the district-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Fixed Effects Sensitivity Analysis: Binned specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<18	-1.4240***	-0.5207	-1.3429**	-0.6026	-0.5142	-0.9113*	-1.2659***
	(0.4623)	(0.5832)	(0.5596)	(0.6087)	(0.5494)	(0.5350)	(0.4717)
18-21	-0.2508	-0.2127	-0.5277	0.0480	-0.0321	-0.1210	-0.3044
	(0.3095)	(0.3493)	(0.3655)	(0.3574)	(0.3368)	(0.3216)	(0.3124)
24-27	-0.2863	-0.1224	0.1734	-0.3743	-0.1654	-0.2688	0.0238
	(0.2272)	(0.3124)	(0.3021)	(0.2742)	(0.2545)	(0.2514)	(0.2436)
27-30	-0.2992	0.1995	0.4900	-0.0984	0.0008	-0.0607	0.1807
	(0.2267)	(0.3355)	(0.3550)	(0.3039)	(0.2890)	(0.2769)	(0.2659)
30-33	-0.5600**	0.4625	0.5080	0.0168	0.2066	0.0765	0.1020
	(0.2260)	(0.3583)	(0.3637)	(0.3255)	(0.3196)	(0.2942)	(0.2721)
33-36	-0.6045**	0.5359	0.6138	-0.0181	0.0849	0.0968	0.2290
	(0.2593)	(0.4252)	(0.4259)	(0.3724)	(0.3747)	(0.3397)	(0.3120)
36-39	-0.3436	0.9152*	1.3334***	0.1031	0.2692	0.2220	0.6041
	(0.3249)	(0.4750)	(0.4879)	(0.4380)	(0.4564)	(0.3958)	(0.3725)
39+	0.3759	1.6192***	2.0607***	0.9416*	0.9986*	0.8758*	1.4013***
	(0.3028)	(0.5975)	(0.5814)	(0.5195)	(0.5337)	(0.4637)	(0.3944)
Outcome mean	17.96	17.97	17.97	17.97	17.96	17.97	17.96
Outcome SD	38.39	38.40	38.40	38.39	38.39	38.39	38.39
R-squared	0.27	0.16	0.15	0.38	0.29	0.28	0.27
N	910318	912360	912449	882489	910068	910231	910318
Trial controls	X	X	X	X	X	X	X
Day of week FE	X	X	X	X		X	
Judge FE	X	X	X		X	X	X
District-month FE		X			X	X	
Judge-month FE				X			
District FE			X	X			
Year FE				X	X	X	X
Year-month FE			X				
Date FE					X		
Month FE					X		X

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear and threshold specifications. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day. Trial controls include crime type, defendant gender, and trial duration. Each specification contains various other fixed effects as indicated. Note that Column (9) is our main specification in Table 2. Standard errors are clustered at the district-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: The effect of daily maximum temperature on conviction rate: robustness to clustering

	Linear			Threshold		
	(1)	(2)	(3)	(4)	(5)	(6)
Temp	0.0633***	0.0633***	0.0633***			
	(0.0173)	(0.0238)	(0.0189)			
Temp $\geq$ 37.7C				1.1070***	1.1070***	1.1070***
				(0.2326)	(0.2917)	(0.2442)
Outcome mean	17.96	17.96	17.96	17.96	17.96	17.96
Outcome SD	38.39	38.39	38.39	38.39	38.39	38.39
R-squared	0.27	0.27	0.27	0.27	0.27	0.27
N	910318	910318	910318	910318	910318	910318
Level of clustering:						
District by month	X			X		
District only		X			X	
Judge only			X			X

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear, nonlinear, and threshold specifications and test their robustness to different ways of clustering the standard errors. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (crime type, defendant gender, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: The effect of daily maximum temperature on conviction rate: alternative outcome definition

	Linear		Threshold		Binned	
	(1)	(2)	(3)	(4)	(5)	(6)
Temp	0.0300***	0.0304***				
	(0.0110)	(0.0110)				
Temp $\geq$ 37.7C			0.5482***	0.5624***		
			(0.1948)	(0.1949)		
<18					-0.0987	-0.0760
					(0.2048)	(0.2048)
18-21					0.2528	0.2809
					(0.1793)	(0.1799)
24-27					0.1787	0.1877
					(0.1449)	(0.1451)
27-30					0.1010	0.1045
					(0.1711)	(0.1711)
30-33					0.1665	0.1780
					(0.1647)	(0.1648)
33-36					0.1673	0.1761
					(0.1887)	(0.1888)
36-39					0.6223***	0.6374***
					(0.2382)	(0.2384)
39+					0.8855***	0.9090***
					(0.2964)	(0.2966)
Outcome mean	7.45	7.45	7.45	7.45	7.45	7.45
Outcome SD	26.25	26.25	26.25	26.25	26.25	26.25
R-squared	0.24	0.24	0.24	0.24	0.24	0.24
N	2222518	2222518	2222518	2222518	2222518	2222518
Trial controls		X		X		X

Note: Sample is restricted to cases with dispositions of conviction, prison, fine, reject, acquitted, appeal, accepted, decided, disposed, judgment, probation, stayed, transferred, 258 crpc (acquittal), and referred to lok adalat. This selection of dispositions closely follows Ash et al. (2022), but we exclude dispositions for which the judge might not the primary decision-maker (e.g., plead guilty, withdrawn, and other). The dependent variable is a binary measure that equals one if the defendant case's disposition is conviction or prison, and 0 otherwise. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day. Trial controls include defendant gender, crime type, and trial duration. The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level.

Table A6: The effect of the number of trial days with temperature above 37.7C on conviction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Num. of trial days w/ temp. $\geq$ 37.7C	0.0755***	0.0688***	0.0693***	0.0768***	0.0746***	0.0775***	0.0774***
	(0.0021)	(0.0020)	(0.0020)	(0.0023)	(0.0020)	(0.0021)	(0.0022)
Outcome mean	17.96	17.97	17.97	17.97	17.96	17.97	17.96
Outcome SD	38.39	38.40	38.40	38.39	38.39	38.39	38.39
R-squared	0.28	0.17	0.15	0.38	0.29	0.29	0.27
N	910318	912360	912449	882489	910068	910231	910318
Trial controls	X	X	X	X	X	X	X
Day of week FE	X	X	X	X		X	
Judge FE	X	X	X		X	X	X
District-month FE		X			X	X	
Judge-month FE				X			
District FE			X	X			
Year FE				X	X	X	X
Year-month FE			X				
Date FE					X		
Month FE					X		X

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear and threshold specifications. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day. Trial controls include crime type, defendant gender, and trial duration. Each specification contains various other fixed effects as indicated. Note that Column (9) is our main specification in Table 2. Standard errors are clustered at the district-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: The effect of daily maximum WBGT on conviction

	Linear		Threshold		Binned	
	(1)	(2)	(3)	(4)	(5)	(6)
WBGT	0.0480**	0.0419*				
	(0.0243)	(0.0238)				
WBGT $\geq$ 32C			0.7702**	0.7925**		
			(0.3759)	(0.3734)		
<18					-0.4212*	-0.3720
					(0.2469)	(0.2423)
21-24					0.1890	0.1424
					(0.2150)	(0.2090)
24-27					0.0398	-0.0044
					(0.2460)	(0.2400)
27-30					0.1420	0.0705
					(0.2657)	(0.2595)
30-33					0.5110	0.4245
					(0.3601)	(0.3514)
33+					1.4020**	1.4237**
					(0.6255)	(0.6202)
Outcome mean	17.96	17.96	17.96	17.96	17.96	17.96
Outcome SD	38.39	38.39	38.39	38.39	38.39	38.39
R-squared	0.26	0.27	0.26	0.27	0.26	0.27
N	910318	910318	910318	910318	910318	910318
Trial controls		X		X		X

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. Wet bulb globe temperature (WBGT) is constructed using the formula from Lemke and Kjellstrom (2012). In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day. Trial controls include defendant gender, crime type, and trial duration. The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A8: The effect of daily maximum temperature on conviction rate: heterogeneous effects by pollution

	Linear		Threshold		Binned	
	high	low	high	low	high	low
	(1)	(2)	(3)	(4)	(5)	(6)
Daily max temperature in C (Temp)	0.0809***	0.1083***				
	(0.0240)	(0.0272)				
Temp $\geq$ 37.7C			0.9639***	1.3821***		
			(0.3138)	(0.3358)		
<18					-1.0675**	-4.6607**
					(0.4991)	(1.8262)
18-21					-0.3128	-0.5142
					(0.3264)	(1.0190)
24-27					0.3022	-0.6842
					(0.2672)	(0.5257)
27-30					0.5506*	-0.4841
					(0.3051)	(0.5306)
30-33					0.3498	-0.3141
					(0.3363)	(0.5404)
33-36					0.1999	0.3803
					(0.3767)	(0.5976)
36-39					0.6155	0.7083
					(0.4715)	(0.6400)
39+					1.5190***	1.3603**
					(0.5165)	(0.6702)
Outcome mean	16.59	19.35	16.59	19.35	16.59	19.35
Outcome SD	37.20	39.50	37.20	39.50	37.20	39.50
R-squared	0.27	0.29	0.27	0.29	0.27	0.29
N	453853	453373	453853	453373	453853	453373

Note: Sample is restricted to cases with dispositions of conviction or acquittal. The dependent variable is a binary measure that equals one if the defendant is convicted and equals 0 if the defendant is acquitted. We scaled this measure by 100 so that the conviction rate can be expressed as a percent rather than as a fraction. We present results from estimation of the linear, nonlinear, and threshold specifications by pollution and different relative humidity measures. We split the sample to court decisions with pollution above (high) or below (low) the median in our sample. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and trial controls (crime type, defendant gender, and trial duration). The regressions include year, month, district, and judge fixed effects as well. Standard errors are clustered at the district-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.