# 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 over 3 million judicial outcomes from the Indian eCourt platform, merged with high-resolution gridded daily weather data. We estimate causal effects leveraging a fixed effects framework. We find that high daily maximum temperatures raise the likelihood of convictions. Our results are robust to numerous controls and specification changes. 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 cognitive performance and productivity, 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), heuristics reliance (Cheema and Patrick, 2012) and productivity (Behrer et al., 2021; Heyes and Saberian, 2022). Impacts of high temperature have also been detected as correlates of mood (Baylis, 2020; Denissen et al., 2008) and happiness (Rehdanz and Maddison, 2005).

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 rate of convictions 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 it is a tropical country that frequently experiences extreme heat.

We take advantage of rich data from the Indian eCourt platform.[1] These data cover the universe of district-level and subordinate courts, which are less likely to have climate-control infrastructure in place (Chandrashekaran et al., 2021). We then merge this information with district-level daily temperature constructed from the ERA5 gridded weather data (Hersbach et al., 2020). We use a linear probability framework to estimate how maximum daily temperatures impact the probability of a conviction, conditional on defendant demograph-

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

ics, weather and pollution characteristics, time and location 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 these 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 0.57 percentage points, which is an 8.8% increase, relative to the baseline conviction rate of 0.065. We also uncover statistically significant nonlinear effects of extreme heat for cases related to violent crimes and other crimes such as abatement, disturbed public health/tranquility, and criminal conspiracy. We explore heterogeneous effects of the impact of higher temperature on convictions by judge's and defendant's gender. We find that high temperatures increase the conviction rates of female judges in particular. This is consistent with earlier work that documents that stress may have a greater negative impact on cognition for women, relative to men, in certain contexts (Yi et al., 2021). We interpret all of our findings as general equilibrium effects given that we cannot ascertain from the data whether convictions ensue directly from climate-driven effects of the behavior of during the trial of the witnesses, defendants, prosecutors, judges, or some combination of these parties. Nevertheless, our findings show that rising temperatures in India help explain negative outcomes for defendants in general.

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. Low- and middle-income countries are projected to face earlier emergence of climate-change-induced heat extremes (Harrington et al., 2016) and are less likely to have widespread access to cooling technologies.

Within this literature, our study is closest in spirit to research that links judicial outcomes and high temperatures in Texas (Behrer and Bolotnyy, 2022), Australia (Evans and Siminski, 2021), and the United States (Heyes and Saberian, 2019). Our study differs in two important dimensions from these studies. First, we focus on district and subordinate courts in India. These courts are less likely to have access to climate-control infrastructure to protect them from heat extremes compared to courtrooms in the United States or Australia. Moreover, 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). Furthermore, by juxtaposing our findings with the earlier literature on developed nations, we hope to provide additional insight into the unequal burden climate change delivers conditional on a country's level of development.

Second, our study offers temporal differences in the analysis of criminal convictions. Even though Behrer and Bolotnyy (2022) and Evans and Siminski (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.[2]

Our results suggest that climate-induced increases in frequency of extreme heat may trigger further increases in probability of convictions, especially for hot tropical countries like India. It is unlikely that this increase in judicial harshness is optimal, since existing

[2]For example, Behrer and Bolotnyy (2022) point out that police officers are more likely to make arrests that judges decide to dismiss on hot days.

research demonstrates that extreme heat impairs cognitive performance (Graff Zivin et al., 2018; Park, 2022), reduces productivity (Behrer et al., 2021), increases impatience (Carias et al., 2021), and increases observable correlates 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. Our results are also relevant in the context of proposed reforms to the Indian judicial system, because they suggest that better access to cooling technologies may reduce the harshness of the judicial system.

The remainder of the paper proceeds as follows: Section 2 outlines the existing literature on the impact of temperature on various outcomes. Section 3 discusses judicial decision-making in the Indian context. Section 4 describes the data and presents summary statistics for the outcomes and control variables. Section 5 provides an overview of the empirical strategy. Section 6 discusses the main findings and sensitivity checks. Section 7 summarizes the main findings and outlines implications for policy.

## 2 Literature Review

Hotter outdoor temperatures appear to have important physiological and psychological effects—even for individuals indoors—with links found on mood (Baylis, 2020; Denissen et al., 2008; Hirshleifer and Shumway, 2003; Cao and Wei, 2005; Floros, 2011), completion of simple and complex tasks (Cheema and Patrick, 2012; Fang et al., 2004; Wyon et al., 1996), labor and firm productivity (Behrer et al., 2021; Heyes and Saberian, 2022; Zhang et al., 2018; Chen and Yang, 2019; Graff Zivin and Neidell, 2014), and cognitive performance (Hancock and Vasmatzidis, 2003; Graff Zivin et al., 2018; Park, 2022; Zivin et al., 2020). Using geo-located tweets from the social media platform, Twitter, Baylis (2020) finds evidence that negative mood metrics (e.g., profanity) tend to increase when outdoor temperatures exceed 70°F (21.11°C). In a laboratory experiment, Cheema and Patrick (2012) find that subjects are less likely to take complex gambles, less likely to choose less established products, and are less likely to adopt non-heuristic methods of processing data. Heyes and Saberian (2022) show that a hot day with temperatures over 37.7°C (99.9°F) lowers the ability to work by 7% in India.[3] For cognitive performance, Park (2022) concludes that in New York City, taking high school exit exams on a day when the outdoor temperature is 90°F (32.22°C) lowers test scores by close to 0.20 standard deviations compared to counterparts who take the exam when the outdoor temperature is 72°F (22.22°C).

Judges respond markedly to workplace disruptions and other extraneous factors when deciding on case dispositions and sentencing outcomes (Philippe and Ouss, 2018; Eren and Mocan, 2018; Danziger et al., 2011; Shumway and Wilson, 2022; Englich and Soder, 2009; Simon, 2012; Dijksterhuis et al., 1996; Wyer and Carlston, 2018; Guthrie et al., 2007).[4] For instance, Eren and Mocan (2018) find that an unforeseen loss in a local football game increases juvenile court sentences handed down by judges by nearly 6.5 percent. More recent studies proliferate the theory that extraneous factors work to sway judicial decision-making, and thereby case outcomes. Shumway and Wilson (2022) find that workplace disruptions through exogenous increases in caseloads produce a one percent decline in favorable judicial outcomes, reducing the number of claimants awarded disability insurance by 16,600. These studies emphasize the role that seemingly irrelevant factors play in influencing judicial outcomes in general. We add to this literature by showing that temperature shocks can influence convictions in India – a context where hot temperatures are commonplace even while climate-control infrastructure inside courtrooms is limited (Chandrashekaran et al., 2021).

Prior literature has found that temperature is an extraneous factor that influences judicial-decision making. Using data on asylum applications to immigration courts across the United States, Heyes and Saberian (2019) find that a 10°F increase in temperature reduces the odds

[3] A meta-analysis finds a near 10% drop in productivity when indoor temperature rises from 71.5°F (21.75°C) to 86.1°F (30°C) (Seppanen et al., 2006).

[4] Bielen and Grajzl (2021) provide evidence that salient extraneous events also affect prosecutors' behavior and decision-making.

of a favorable decision in immigrant adjudications by approximately 7 percent. Behrer and Bolotnyy (2022) finds that on hotter days judges in Texas hand down longer prison sentences conditional on conviction. The authors also find that arrests rise significantly on hot days in response to the rise in violent crime, which might conflate the estimated effect on sentencing.[5] However, not all studies find economically meaningful effects of outdoor temperatures on justice-related outcomes. Evans and Siminski (2021) show that the effect of outdoor temperatures on court case decisions is precisely estimated to be zero using data from the Australian state of New South Wales. However, Australia may be uniquely different from other countries. Johnston et al. (2021) find that cold weather shocks lower test scores of Australian students between the ages of 8 and 15 years old; in contrast, hotter temperatures in the previous year did not change cognitive performance statistically significantly.

Relative to this existing literature, our study's focus on India represents an important contribution. Climate-control infrastructure to protect from extreme heat is less accessible in India compared to high-income countries. As such, temperature is likely to influence a variety of outcomes including judicial decisions. The literature provides robust support for this hypothesis. Studies conclude that rising temperatures have led to declines in labor productivity in the manufacturing sector (Somanathan et al., 2021), economic output (Jain et al., 2020), household consumption (Aggarwal, 2021) and human capital accumulation in India (Garg et al., 2020). Importantly, existing work has found that the negative impacts of high temperatures are significantly greater in India than high-income countries. For example, Garg et al. (2020) find significant effects of longer-run effects high temperatures on human capital accumulation in India, whereas as similar study in the U.S. by Graff Zivin et al. (2018) fails to detect longer-run impacts of temperature on human capital. In a similar vein, Jain et al. (2020) find than a 1°C increase temperature reduces economic growth rates by 2.5 percentage points in India, an effect that is roughly five times larger than the impact found in a comparable study in the U.S. by Colacito et al. (2019).

[5] We note that in India, there is a significant backlog of court cases, which means that there is a significant temporal gap between the dates of arrest and conviction.

In summary, the existing literature demonstrates that high temperatures have significant negative impacts on our mood and cognition. Existing literature also demonstrates that judicial opinions are swayed by a variety of extraneous factors, including temperature. And, researchers have found significant negative impacts of high temperatures in India on a variety of outcomes— including labor productivity, economic output, and households consumption— often with magnitudes that exceed those of high-income countries. Based on these findings, we hypothesize that hotter temperatures in India will produce harsher judicial outcomes.

# 3 Institutional Detail

The Indian judicial system is comprised of three levels: district-level and subordinate courts, a High Court in each state, and a single federal Supreme Court. We focus on district-level and subordinate courts, which fall under the purview of individual state governments, and are also less likely to be equipped with climate-control infrastructure such as air-conditioning (Chandrashekaran et al., 2021).

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. Muslims are similarly underrepresented: they comprise 14% of population but fill only 7% of district judge seats (Ash et al., 2022). Judges have a significant margin of subjectivity in their rulings and research suggests that judge 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 according to Ash et al. (2022).[6] 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.

# 4 Data

Our analyses link judicial data from the Indian eCourts platform to daily temperature data agglomerated at the district-level. The Indian eCourts platform is a partially-public data warehouse made available by the Indian government; it is comprised of approximately 77 million Indian court cases. We exploit the data made publicly available – case filings, registration, hearings, defendant characteristics and 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.[7] Our final estimation sample consists of approximately 3.1 million case records from 2010 to 2018.

[6]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.

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

Having restricted our sample to criminal cases, we next restrict our samples to outcomes in which the judge was the final decision maker. This means that we exclude cases with dispositions such as confession, died, or plead guilty, because these are not court outcomes in which the judge is the ultimate decision maker; we are interested in the impact of higher temperatures on judicial decision-making. Finally having restricted the cases to those in which the judge is the final decision-maker, we define a conviction as simply a binary indicator equal to 1 if the defendant was convicted for the offense by the judge.

Table 1 presents the summary statistics for our sample. The table indicates that about 6.5% of the defendants in the sample are convicted. As it relates to defendant and judge characteristics – about 10% of defendants are women and nearly 70% of judges are men. For type of criminal offenses in the sample: close to 40% of offenses are violent crimes, while 16% and 32% of the analysis sample are property and other crimes, respectively. The additional 15% of the sample are crimes that we are unable to classify or crimes with missing penal section information.[8]

We use information from the ERA5 gridded weather dataset (Hersbach et al., 2020) to construct our variable of interest – maximum daily temperatures – and precipitation measured at the district level. The ERA5 gridded weather dataset provides detailed weather information on the degree-specific longitude and latitude grid from 1979 to 2018. In addition, 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.[9] 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). Table 1 indicates that

[8]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 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 while other crimes include. Other crimes include crimes such as abatement, criminal conspiracy, disturbed public health/tranquility, crimes against the state/army, election crimes, etc.

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

the average maximum daily temperature over the study period (2010-2018) is 29.7 °C. We also consolidate maximum daily temperatures in bins with width 3°C. As Figure 1 illustrates, maximum daily temperatures in India are considerably left-skewed, with the modal temperatures ranging from 27°C to 30°C.

# 5 Empirical Framework

To examine the relationship between 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.[10] $Convicted_{ijkdmy}$ represents the binary measure equal to 1 if the defendant was convicted of a crime and 0 otherwise. 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. 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 on climate change impacts demonstrates the existence of important non-linearities in temperature impacts, which motivates our use of our next two specifications.

[10] 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 A4 we conduct a sensitivity check to test the validity of this assumption, by analyzing temperature over the entire trial period instead of just temperature on the decision date. See Section 6 for further discussion.

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

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

Here, our temperature specification is a binary indicator that equals 1 if the daily maximum temperature on the decision date exceeded 37.7°C, and equals 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.[11] We estimate separate coefficients for each of these nine bins and we omit the bin 21–24°C as our reference category to avoid collinearity. 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 maximum daily temperature will lead to increased rates of convictions. In other words, we expect

[11] 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.

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 $j$.

$W_{kdmy}$ 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 $\eta_j, \eta_k, \eta_m$ and $\eta_y$ capture judge fixed effects, district fixed effects, month fixed effects, and year fixed effects, respectively.

$\epsilon_{ijkdmy}$ is a spatially and serially correlated error term. Following the recommendations of Abadie et al. (2017), 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. This model thus serves our identifying assumption that once we control for court, date, time, weather, and pollution controls, the effect of maximum daily temperature on judicial outcomes will be *as-good-as-random*.

# 6 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 0.2 percentage points ($p < 0.05$) when temperature rises by 10°C. Adding trial characteristics to the model raises the probability of a conviction by 0.3 percentage points ($p < 0.01$) in response to a rise in temperature of 10°C. Although these estimates may appear negligible in absolute magnitude, when we compare them to the conviction mean (0.065), the evidence suggests that when daily maximum temperature rises by 10°C, the probability of a conviction increases by up to about 5 percent.

To show the significance of extreme temperatures, 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 0.45 and 0.57 percentage points ($p < 0.01$), respectively, relative to days with the maximum temperature below 37.7°C. In comparison to the corresponding mean, the evidence suggests that on days with maximum temperatures above 37.7°C the conviction probability increases by 6.9 % to 8.8%.

In addition to estimating linear and threshold effects, we examine possible non-linear relationships in Columns (5) and (6) in Table 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 0.46 percentage points ($p < 0.05$) higher when temperatures are above 36-39°C range compared to when the temperature is within the 21-24°C range. Moreover, the probability of receiving a conviction is 0.71 percentage points ($p < 0.01$) higher when temperatures are above 39°C. With trial controls, the probability of receiving a conviction is 0.66 percentage points ($p < 0.01$) higher when temperatures are in the 33-36°C range, and 0.93 percentage points ($p < 0.01$) higher when temperatures are above 39°C. When compared to the conviction mean, the evidence suggests that higher daily maximum temperatures account for approximately a 7-14% increase in the likelihood of a conviction. Figure 2 graphically depicts the binned specification results from Table 2. The plotted coefficient estimates display the relative change in the probability of each outcome compared to the excluded category of 21-24°C. Binned temperatures cooler than the excluded category do not appear to yield statistically different results from the excluded category; however, higher daily maximum temperatures appear to produce increasingly larger changes in the likelihood of a conviction. This illustration suggests that as daily maximum temperatures draw closer to 39°C and above , the larger the positive effect on the probability of a conviction.

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. A recent literature shows that extreme heat impairs cognitive performance (Graff Zivin et al., 2018; Park, 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. The table shows that the impact of high temperatures on the probability of conviction is positive and statistically significant for violent crimes and other crimes, with impact estimates rising with temperature (see Figure A2). We do not detect a statistically significant effect of high temperatures on conviction rates in property crime cases. 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 odds of conviction do not serve as proxy for estimates on crime.

Table 4 presents the impact of the gender of the judge on the probability of a conviction. The evidence shows that female judges are more susceptible to temperature extremes – all three temperature specifications indicate that female judges are more likely to issue a conviction as temperatures rise. In contrast, we do not detect a statistically significant effect of high temperatures on conviction rates for male judges. Our heterogeneous findings by judge gender are consistent with earlier work that documents, first, that women are at a thermoregulatory disadvantage under extreme heat stress, relative to men, (Cheung et al., 2000; Corbett et al., 2020) and, second, that, 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).

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. We do not detect statistically significant differences in the impact of temperature on conviction rates by defendant gender. This absence of a statistically significant difference is sensible, given that we are focusing on an outcome that the judge, rather that the defendant, has control over.

Finally, we conduct some sensitivity analyses to test the robustness of our results. First, we test the sensitivity of our results to multiple sets of fixed effects, in Appendix Table A2 (which explores our linear and threshold models) and in Appendix Table A3 (which 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 main findings.

Second, 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. 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 A4 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, falls by about a factor of ten. This finding is not surprising given that temperatures over the course of the trial may influence the judge, but are unlikely to surpass temperatures effects on the actual decision date.

# 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 the Indian context. We exploit data from the Indian eCourt platform (2010–2018) merged with high-resolution daily maximum temperature data to evaluate this research problem. Using three different specifications, we find that rising temperatures statistically significantly increase the likelihood of convictions, and these effect appear to be highly non-linear. We also uncover that temperature-driven convictions are largely for violent crimes and that higher temperatures increase the rates of conviction for female judges in particular. Overall, our results document that conviction rates are higher on hotter days. 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 existing research that extreme heat leads to reductions in cognitive performance (Graff Zivin et al., 2018; 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 has focused on high-income countries (United States, Australia) and, furthermore has found mixed results: some studies have found that high temperatures increase judicial harshness (Heyes and Saberian, 2019; Behrer and Bolotnyy, 2022), while others have failed to detect such an effect (Evans and Siminski, 2021). We contribute significantly to this body of work, because we study judicial outcomes in a lower-middle-income country, in a setting where we could expect temperature impacts to be magnified, due to higher baseline heat exposure and limited access to cooling technology. Our findings may, as a result, be applicable to other low- or middle- income countries that face a similar heat burden, court structure, or level of infrastructure. More broadly, our findings contribute to the growing literature showing that rising temperatures are linked to more adverse outcomes in low- and middle-income countries (Ricke et al., 2018; Diffenbaugh and Burke, 2019; Somanathan et al., 2021).

Our findings are policy-relevant, and suggest that improving access to cooling technologies in courthouses in India and similar countries should be a high priority, since convictions are high-stake decisions with life-changing impacts for defendants and society as a whole. Our results also 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 a currently a point of critical concern. Future research could explore whether higher temperatures reduce judge's 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.

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# Figures

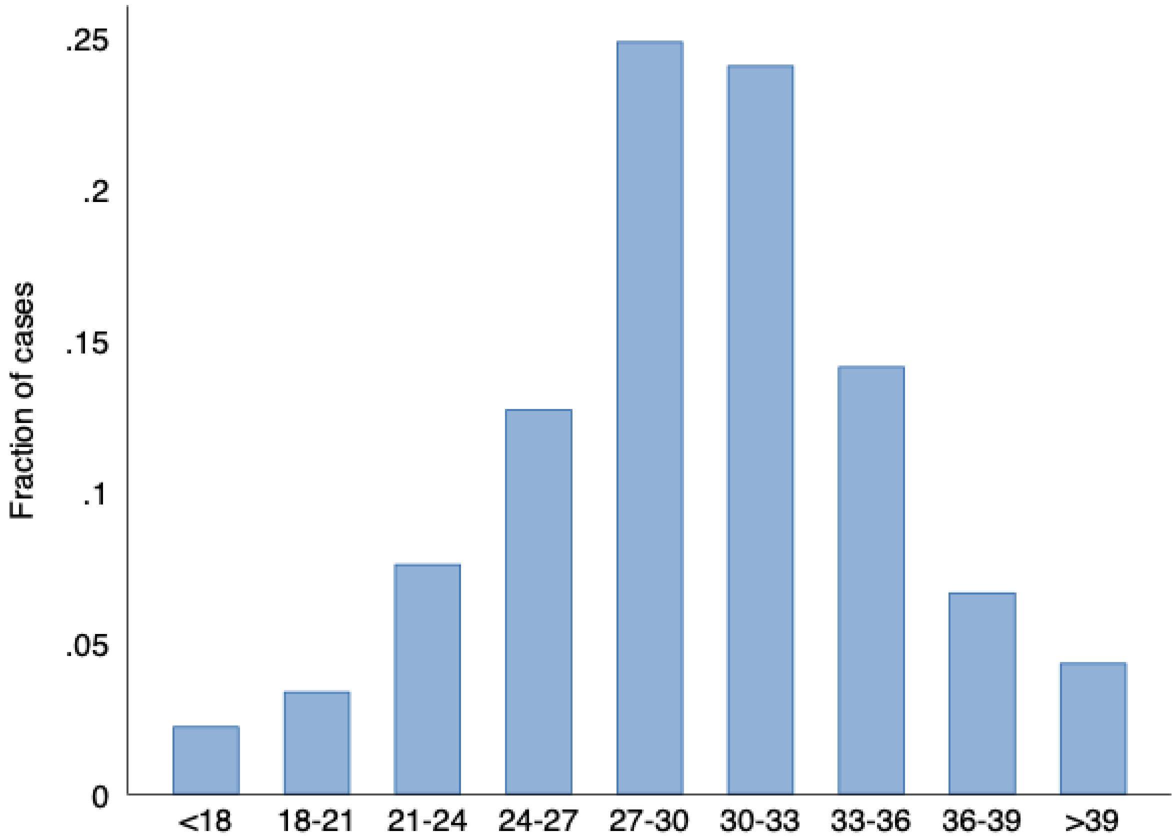



Figure 1: Distribution of Daily Maximum Temperature for Court Cases

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

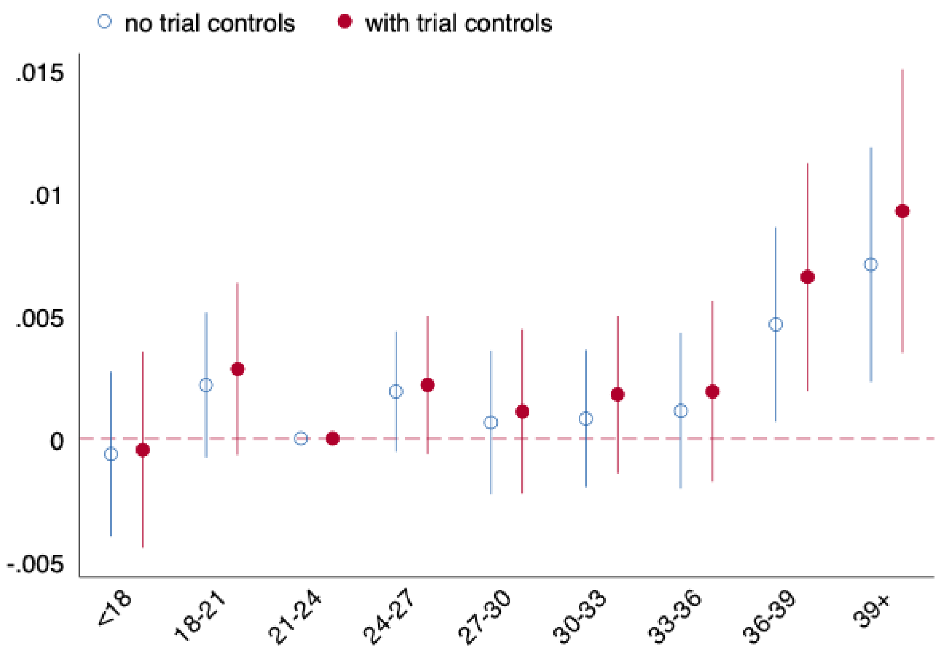



Figure 2: The effect of daily maximum temperature on conviction: nonlinear estimates

*Note*: This figure plots the coefficient estimates and their 95% confidence interval bands on the temperature indicator variables from estimation of the nonlinear specification. 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.

# Tables

Table 1: Summary statistics

| | Mean | S.D. |
|---|---|---|
| Convicted | 0.065 | 0.246 |
| Daily max temperature in C (Temp) | 29.737 | 5.379 |
| Temp $\geq$ 37.7 | 0.068 | 0.253 |
| Mean daily temperature (C) | 25.963 | 5.431 |
| Total daily precipitation (mm) | 3.306 | 8.896 |
| Mean daily PM2.5 | 88.868 | 70.451 |
| Female defendant | 0.104 | 0.305 |
| Male defendant | 0.896 | 0.305 |
| Trial duration (days) | 515.767 | 611.643 |
| Female judge | 0.281 | 0.449 |
| Male judge | 0.687 | 0.464 |
| Violent crime | 0.382 | 0.486 |
| Property crime | 0.158 | 0.364 |
| Other crime | 0.316 | 0.465 |
| Missing crime type | 0.145 | 0.352 |
| N | 2,888,856 | |

*Note*: This table presents summary statistics of our estimation sample described in Section 4. All weather and pollution variables are measured on the day of the conviction decision.

Table 2: The effect of daily maximum temperature on conviction

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Temp | 0.0002** | 0.0003*** | | | | |
| | (0.0001) | (0.0001) | | | | |
| Temp $\geq$ 37.7 | | | 0.0045*** | 0.0057*** | | |
| | | | (0.0016) | (0.0019) | | |
| <18 | | | | | -0.0006 | -0.0005 |
| | | | | | (0.0017) | (0.0020) |
| 18-21 | | | | | 0.0022 | 0.0028 |
| | | | | | (0.0015) | (0.0018) |
| 24-27 | | | | | 0.0019 | 0.0022 |
| | | | | | (0.0013) | (0.0014) |
| 27-30 | | | | | 0.0007 | 0.0011 |
| | | | | | (0.0015) | (0.0017) |
| 30-33 | | | | | 0.0008 | 0.0018 |
| | | | | | (0.0014) | (0.0016) |
| 33-36 | | | | | 0.0011 | 0.0019 |
| | | | | | (0.0016) | (0.0019) |
| 36-39 | | | | | 0.0046** | 0.0066*** |
| | | | | | (0.0020) | (0.0024) |
| 39+ | | | | | 0.0071*** | 0.0093*** |
| | | | | | (0.0024) | (0.0030) |
| Observations | 2888703 | 2220916 | 2888703 | 2220916 | 2888703 | 2220916 |
| $R^2$ | 0.235 | 0.239 | 0.235 | 0.239 | 0.235 | 0.239 |
| Trial controls | | X | | X | | X |

*Note*: The dependent variable is probability of conviction. 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 3: The effect of daily maximum temperature on conviction by crime type

| | Linear | | | Nonlinear | | | Threshold | | |
|---|---|---|---|---|---|---|---|---|---|
| | Violent | Property | Other | Violent | Property | Other | Violent | Property | Other |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Temp | 0.0004*** | 0.0002 | 0.0002 | | | | | | |
| | (0.0002) | (0.0003) | (0.0002) | | | | | | |
| Temp<37.7 | | | | 0.0073** | 0.0007 | 0.0066*** | | | |
| | | | | (0.0036) | (0.0035) | (0.0021) | | | |
| <18 | | | | | | | -0.0040 | -0.0059 | 0.0064** |
| | | | | | | | (0.0032) | (0.0051) | (0.0031) |
| 18-21 | | | | | | | -0.0019 | 0.0104*** | 0.0061** |
| | | | | | | | (0.0025) | (0.0040) | (0.0025) |
| 24-27 | | | | | | | 0.0010 | 0.0017 | 0.0016 |
| | | | | | | | (0.0021) | (0.0036) | (0.0024) |
| 27-30 | | | | | | | 0.0005 | 0.0052 | 0.0004 |
| | | | | | | | (0.0025) | (0.0039) | (0.0026) |
| 30-33 | | | | | | | 0.0019 | 0.0059 | -0.0002 |
| | | | | | | | (0.0023) | (0.0040) | (0.0026) |
| 33-36 | | | | | | | 0.0004 | 0.0034 | 0.0038 |
| | | | | | | | (0.0029) | (0.0045) | (0.0028) |
| 36-39 | | | | | | | 0.0059* | 0.0078 | 0.0084** |
| | | | | | | | (0.0033) | (0.0054) | (0.0038) |
| 39+ | | | | | | | 0.0126** | 0.0040 | 0.0086** |
| | | | | | | | (0.0050) | (0.0061) | (0.0035) |
| Observations | 899829 | 255467 | 691987 | 899829 | 255467 | 691987 | 899829 | 255467 | 691987 |
| $R^2$ | 0.207 | 0.305 | 0.457 | 0.207 | 0.305 | 0.457 | 0.207 | 0.305 | 0.457 |

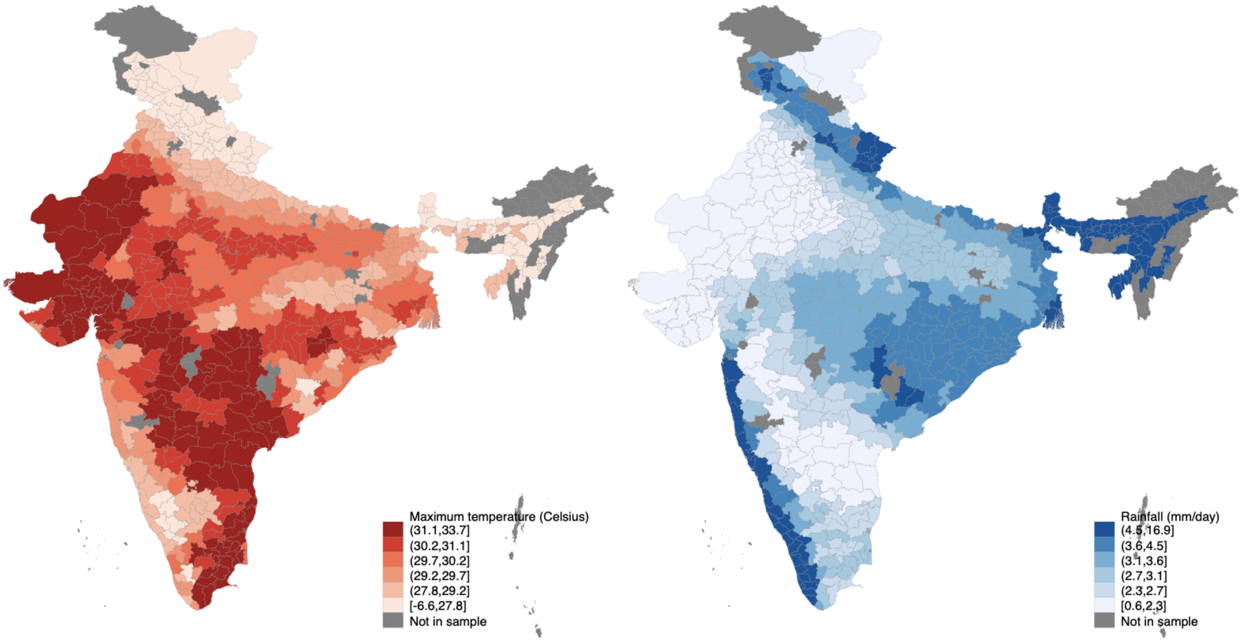
*Note*: The dependent variable is probability of conviction. We present results from estimation of the linear, nonlinear, and threshold specifications by crime type. In all specifications, we control for precipitation and pollution (PM2.5), measured as calendar daily average on the decision day, and 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

| | Linear | | Nonlinear | | Threshold | |
|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Temp | -0.0000 | 0.0005** | | | | |
| | (0.0002) | (0.0002) | | | | |
| Temp $\geq$ 37.7 | | | 0.0017 | 0.0056** | | |
| | | | (0.0017) | (0.0027) | | |
| <18 | | | | | 0.0000 | 0.0011 |
| | | | | | (0.0030) | (0.0041) |
| 18-21 | | | | | 0.0024 | 0.0047 |
| | | | | | (0.0025) | (0.0030) |
| 24-27 | | | | | -0.0001 | -0.0000 |
| | | | | | (0.0018) | (0.0024) |
| 27-30 | | | | | -0.0010 | 0.0024 |
| | | | | | (0.0019) | (0.0027) |
| 30-33 | | | | | -0.0004 | 0.0048 |
| | | | | | (0.0021) | (0.0030) |
| 33-36 | | | | | -0.0014 | 0.0039 |
| | | | | | (0.0024) | (0.0034) |
| 36-39 | | | | | -0.0011 | 0.0090** |
| | | | | | (0.0027) | (0.0040) |
| 39+ | | | | | 0.0007 | 0.0086* |
| | | | | | (0.0031) | (0.0046) |
| Observations | 1506293 | 622913 | 1506293 | 622913 | 1506293 | 622913 |
| $R^2$ | 0.293 | 0.333 | 0.293 | 0.333 | 0.293 | 0.333 |

*Note*: The dependent variable is probability of conviction. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# A Appendix: Supplementary Figures




(a) Annual average maximum temperature

(b) Annual total precipitation

Figure A1: Maps of maximum temperature and total precipitation.

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

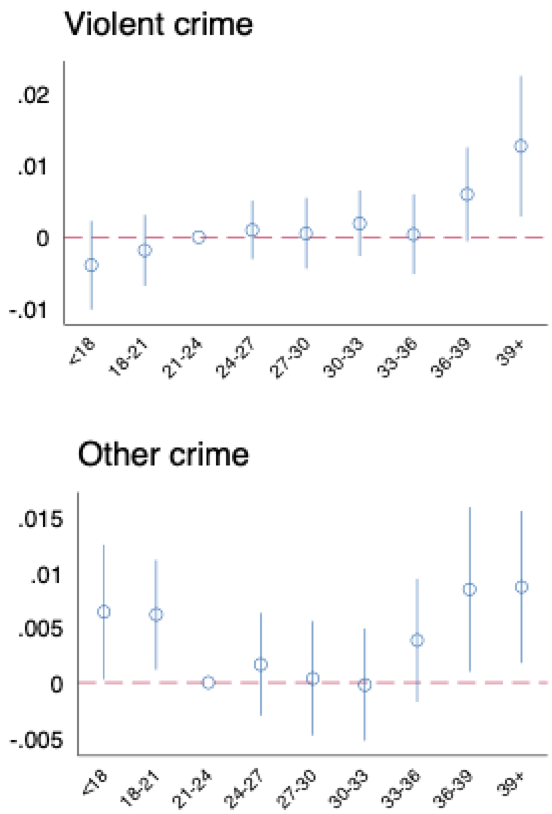



Figure A2: Nonlinear estimates by crime type

*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.

# B Appendix: Supplementary Tables

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

| | Linear | | Nonlinear | | Threshold | |
|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Temp | 0.0002 | 0.0004 | | | | |
| | (0.0001) | (0.0004) | | | | |
| Temp $\geq$ 37.7 | | | 0.0027* | -0.0021 | | |
| | | | (0.0015) | (0.0041) | | |
| <18 | | | | | 0.0010 | -0.0014 |
| | | | | | (0.0025) | (0.0061) |
| 18-21 | | | | | 0.0032 | -0.0005 |
| | | | | | (0.0021) | (0.0045) |
| 24-27 | | | | | -0.0005 | 0.0007 |
| | | | | | (0.0015) | (0.0040) |
| 27-30 | | | | | -0.0006 | 0.0065 |
| | | | | | (0.0017) | (0.0045) |
| 30-33 | | | | | 0.0007 | 0.0054 |
| | | | | | (0.0018) | (0.0049) |
| 33-36 | | | | | -0.0002 | 0.0075 |
| | | | | | (0.0020) | (0.0054) |
| 36-39 | | | | | 0.0014 | 0.0054 |
| | | | | | (0.0023) | (0.0063) |
| 39+ | | | | | 0.0031 | 0.0060 |
| | | | | | (0.0027) | (0.0072) |
| Observations | 1987218 | 220774 | 1987218 | 220774 | 1987218 | 220774 |
| $R^2$ | 0.291 | 0.404 | 0.291 | 0.404 | 0.291 | 0.404 |

*Note*: The dependent variable is probability of conviction. 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) |
| Temp | 0.0001 | 0.0006*** | 0.0005*** | 0.0003** | 0.0004** | 0.0005*** | 0.0003*** |
| | (0.0001) | (0.0002) | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0001) |
| Observations | 2220916 | 2221797 | 2221841 | 2189607 | 2220807 | 2220872 | 2220916 |
| $R^2$ | 0.239 | 0.141 | 0.124 | 0.350 | 0.254 | 0.251 | 0.239 |
| | Threshold specification | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Temp $\geq$ 37.7 | 0.0044** | 0.0040* | 0.0047* | 0.0030** | 0.0020 | 0.0035** | 0.0057*** |
| | (0.0019) | (0.0020) | (0.0024) | (0.0014) | (0.0015) | (0.0014) | (0.0019) |
| Observations | 2220916 | 2221797 | 2221841 | 2189607 | 2220807 | 2220872 | 2220916 |
| $R^2$ | 0.239 | 0.141 | 0.124 | 0.350 | 0.254 | 0.251 | 0.239 |
| 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*: The dependent variable is probability of conviction. 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: Nonlinear specification

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| <18 | -0.0008 | -0.0013 | -0.0011 | 0.0001 | -0.0026 | -0.0007 | -0.0005 |
| | (0.0019) | (0.0024) | (0.0028) | (0.0025) | (0.0027) | (0.0023) | (0.0020) |
| 18-21 | 0.0027 | 0.0027 | 0.0036 | 0.0022 | -0.0012 | 0.0023 | 0.0028 |
| | (0.0017) | (0.0020) | (0.0024) | (0.0020) | (0.0020) | (0.0019) | (0.0018) |
| 24-27 | 0.0013 | 0.0017 | 0.0051** | -0.0008 | 0.0012 | 0.0007 | 0.0022 |
| | (0.0014) | (0.0018) | (0.0021) | (0.0014) | (0.0016) | (0.0014) | (0.0014) |
| 27-30 | -0.0003 | 0.0031 | 0.0051** | -0.0000 | 0.0020 | 0.0016 | 0.0011 |
| | (0.0016) | (0.0020) | (0.0025) | (0.0015) | (0.0018) | (0.0016) | (0.0017) |
| 30-33 | -0.0006 | 0.0048** | 0.0055** | 0.0021 | 0.0038* | 0.0035** | 0.0018 |
| | (0.0014) | (0.0021) | (0.0025) | (0.0017) | (0.0020) | (0.0017) | (0.0016) |
| 33-36 | -0.0009 | 0.0059** | 0.0061** | 0.0013 | 0.0032 | 0.0036* | 0.0019 |
| | (0.0016) | (0.0024) | (0.0028) | (0.0019) | (0.0023) | (0.0019) | (0.0019) |
| 36-39 | 0.0024 | 0.0080*** | 0.0104*** | 0.0022 | 0.0034 | 0.0054** | 0.0066*** |
| | (0.0022) | (0.0029) | (0.0034) | (0.0022) | (0.0027) | (0.0022) | (0.0024) |
| 39+ | 0.0052* | 0.0120*** | 0.0118*** | 0.0048* | 0.0057* | 0.0084*** | 0.0093*** |
| | (0.0028) | (0.0035) | (0.0043) | (0.0025) | (0.0030) | (0.0025) | (0.0030) |
| Observations | 2220916 | 2221797 | 2221841 | 2189607 | 2220807 | 2220872 | 2220916 |
| $R^2$ | 0.239 | 0.141 | 0.124 | 0.350 | 0.254 | 0.251 | 0.239 |
| 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*: The dependent variable is probability of conviction. 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 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. $\geq$ 37.7 | 0.0004*** | 0.0003*** | 0.0003*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Observations | 2220916 | 2221797 | 2221841 | 2189607 | 2220807 | 2220872 | 2220916 |
| $R^2$ | 0.241 | 0.143 | 0.127 | 0.352 | 0.256 | 0.253 | 0.241 |
| 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*: The dependent variable is probability of conviction. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.