The Effect of Outside Temperature on Criminal Court Sentencing Decisions

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Climate change has stimulated growing interest in the influence of temperature on cognition, mood and decision making. This paper is the first investigation of the impact of temperature on the outcomes of criminal court cases. It is motivated by Heyes and Saberian (2019, AEJ: Applied Economics), who found strong effects of temperature on judges' decisions in immigration cases, drawing on 207,000 cases. We apply similar models to analyse 2.8 million criminal court cases in the Australian state of New South Wales from 1994 to 2019. Most of the estimates are precise zeros. We conclude that outcomes of criminal court cases (which are far more prevalent globally than immigration cases) are not influenced by fluctuations in temperature, an unsurprising but reassuring result.

Keywords: criminal courts, temperature, climate, decision making

JEL Codes: K14, K41, Q54

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I. Introduction

The effects of temperature on cognitive performance, mood and decision making have been studied widely for decades.[1] But this topic is becoming increasingly important in the context of climate change. A recent study by Heyes and Saberian (2019) is particularly striking. Using a credible quasi-experimental design, they found very strong causal effects of temperature on the decisions of judges in migration court cases in the United States. For example, an outdoor temperature of 85-90°F on a case date was estimated to reduce the probability of a favourable outcome by 6 percentage points, relative to a 50-55 degree day. As argued by the authors, these results show that if temperature can have such large effects on such significant decisions by experienced judges in an indoor environment, then the overall welfare implications for decision making more generally may be enormous.

At the very least, those results warrant further study in other related settings. For example, do such findings question the credibility of decisions in the closely related setting of criminal courts? This is what motivates our paper. We believe ours is the first paper to estimate the effects of temperature on criminal court outcomes.[2] We consider effects on the probability of a guilty outcome, as well as on the severity of punishment.

On a global scale, the types of crimes we investigate are far more prevalent than the asylum applications researched by Heyes and Saberian (2019). Importantly, existing empirical work suggests that decisions in criminal courts may be just as susceptible as migration courts to idiosyncratic factors such as weather and sporting outcomes (Eren and Mocan, 2018; Chen and Loecher, 2020), timing around meal breaks (Danziger et al., 2011), and irrelevant anchors (Englich et al., 2006).

Adopting a similar identification strategy to Heyes and Saberian (2019), we analyse over 2.8 million criminal court cases held between 1994 and 2019 in the state of New South Wales (NSW). NSW is Australia's largest state, with around one third of the national population.

[1] We review this literature in detail in Section 2.

[2] See also the more recent work by Spamann (2020), whose results are similar to ours. Spamann directly challenges Heyes & Saberian's findings, and extends their analysis to US criminal court cases.

We find little or no evidence of an effect of temperature on court case sentencing, and the estimates are very precise. In the preferred specification, an increase of 10°F raises the probability of a guilty sentence by only 0.04 percentage points, and this is not statistically significant. The 95% confidence interval rules out effects larger than 0.154 percentage points. This zero result holds across many subgroup analyses, including different crime types, different regions and time periods. The results are robust across most (but not all) alternate specifications. We also find no effect on severity of sentencing, and no evidence of nonlinear temperature effects.

The rest of the paper is set out as follows. Section 2 reviews existing literature in this research area. Sections 3 and 4 describe the data and methods, respectively. Section 5 presents the results and Section 6 concludes.

II. Literature Review

This section reviews literature on the effects of indoor temperature and environmental factors on cognition, mood and decision making. It also reviews the work on other idiosyncratic factors affecting court sentencing outcomes.

A. Effects of Indoor Temperature on Cognition

The effect of temperature on cognition and decision making has been studied by a number of disciplines using a range of techniques. Allen and Fischer (1978) is an example of an early study in which indoor temperature was varied experimentally, holding humidity constant. They found that student performance on learning and recall tasks peaked at 72°F (22°C). Decades later, a meta-analysis of 24 similar studies came to essentially the same conclusion (Seppänen *et al.*, 2006).

Cheema and Patrick (2012) found that warmer temperature leads to lower cognitive performance and an increased reliance on heuristic processing, drawing on five separate studies. Warmer temperatures have also been shown to increase consumers' conformity with other decision makers (Huang et al, 2014). This is argued to be a result of lower cognitive processing due to the change in temperature, although results are dependent on the familiarity and relationship of the other decision maker.

B. Outdoor Temperature, Other Environmental Factors and Cognition

Studies on the effects of outdoor temperature on cognition reach broadly similar conclusions (Park, 2016; Graff Zivin *et al.*, 2018). Such work is more directly relevant to studying the potential effects of climate change. On the other hand, researchers are unable to control the outdoor climate, so there is greater risk of confounding from other aspects of weather that are correlated with temperature.

Temperature is not the only weather factor that has an influence on cognition, mood and decision making. Many studies have noted that effects of temperature may be sensitive to controlling for other weather variables (including the early work of Auliciems, 1972 and Allen and Fischer, 1978), highlighting the need to control for such factors. Denissen et al (2008) make similar observations with reference to mood, which we discuss in the next sub-section.

The effects of other environmental factors such as pollution have also been studied extensively. One example is Lavy, Ebenstein and Roth (2014), who explore the impact of plausibly exogenous short-term exposure to ambient pollution on performance on high stakes tests by Israeli students. Fine particulate matter and carbon monoxide both have robust negative effects on test scores.

C. Mood and Productivity

The types of decisions we study may be affected by temperature not only due to cognition, but potentially also by mood and other factors. We briefly discuss these here.

The effect of weather on mood varies greatly between individuals (Klimstra et al, 2011). But it is generally concluded that many aspects of weather influence mood. This is most pronounced in the case of Seasonal Affective Disorder (SAD) (Rosenthal et al, 1984; Terman et al, 1989), which is a change in emotions during a change in weather most commonly occurring during the seasonal change from summer to colder, darker winter months. Howarth and Hoffman (1984) conclude that humidity, temperature and hours of sunshine have the greatest effect on mood. Sinclair *et al.* (1994) found that pleasant days (defined as clear, sunny and warm) elicited more positive responses to a survey completed by college students.

Keller *et al.* (2005) argue that the effects of weather on mood are moderated by the amount of time spent outdoors as well as the season. They found that pleasant weather in Spring improves mood and memory. In contrast, Forgas, *et al.* (2008) found that days with bad weather improved the memories of consumers in a small suburban retail shop in Sydney.

Lee *et al.* (2014) found that bad weather can increase individual productivity. They argue that this occurs due to the elimination of potential distractions associated with good weather. This result was found from a combination of four separate studies including field and lab methods, although two of the studies did not support this hypothesis. Similar to Sinclair *et al.* (1994) they argue that this could be due to external factors such as time spent outside and the amount of activity the individual has exerted that particular day.

D. Effects of Other Idiosyncratic Factors on Court Sentencing

There is evidence that other external, seemingly idiosyncratic, factors can impact decisions made within courts. Phillipe and Ouss (2018) examined the effects of media in the days and weeks leading up to court sentencing. They conclude that media coverage of crime or the justice system has an effect on sentencing decisions, but not convictions. The results also suggest that the amount of professional experience a judge has mitigates the potential effect of the media and the effects are larger on citizens participating in a jury.

Other idiosyncratic factors such as hunger and timing of breaks (Danziger et al., 2011) and randomly assigned sentencing demands which act as an anchor (Englich, Mussweiler & Strack, 2006) can affect court outcomes. Danziger et al. (2011) show that favourable rulings drop before a judge takes a break, with a higher proportion of favourable decisions made in the morning and after food breaks. Chen and Loecher (2019) show that sporting results also have an influence on US court decisions. They show that judges deny more asylum applications and dispense longer prison sentences after a loss of the NFL team they support. Eren and Mocan (2018) find that unexpected losses by the local college football team have large effects on sentencing in juvenile courts.

III. Data

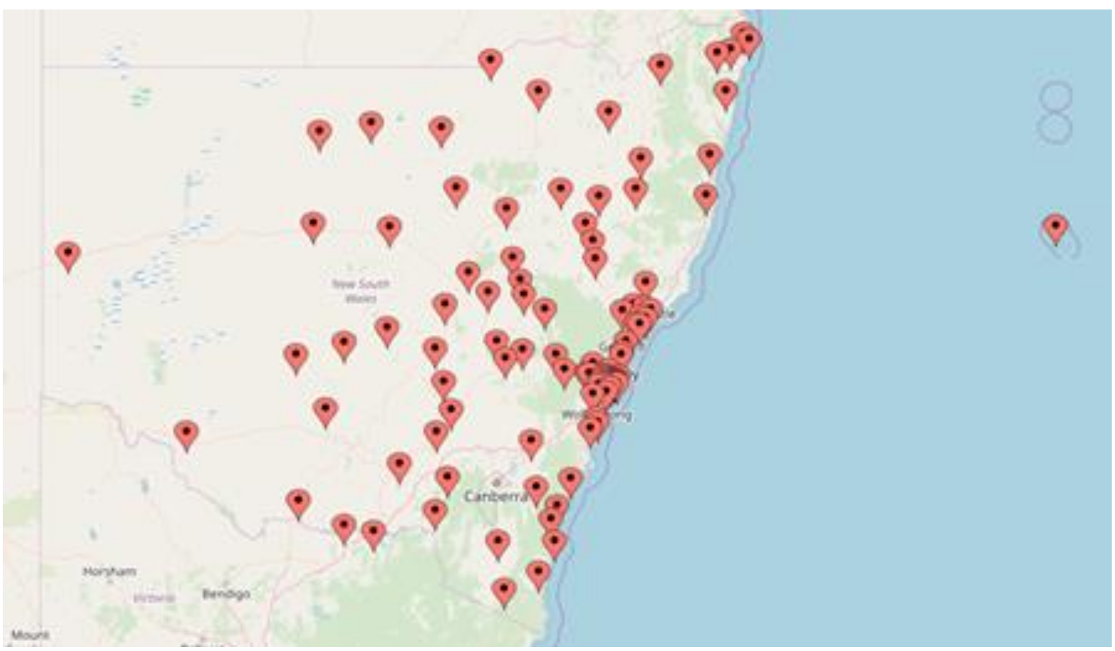
We draw on criminal court microdata from the NSW Bureau of Crime Statistics and Research (BOCSAR), weather data from the Bureau of Meteorology (BoM) and pollution data from the NSW Department of Planning, Industry and Environment. The three data sets are merged by date and location (keeping cases at courts located within 30km of an active weather station) to create one observation per criminal court case heard in NSW from January 1994 to July 2019.

A. Court Data

We draw on microdata which includes case-level criminal court decision from courts in NSW from 1994-2019. The data are from the BOCSAR Re-offenders Database (ROD). The database includes cases held in Local Courts and in District Courts, as well as one Children's Court and the NSW Supreme Court. A Local Court is a lower level court that attends to the majority of cases and is presided over by a magistrate (Local Court Act, 2007). Almost all of these cases were heard by a judge, with no jury.[3]

The data include variables for court location, date of hearing, type of offence, whether the defendant was found guilty, penalty type, and a measure of penalty severity. The data set does not have identifiers for individual judges. The full data obtained contains 3,217,625 observations. The estimation sample consists of 2,817,711 observations once merged with temperature data. The main estimation sample spans 122 court locations, shown in Figure 1.

Figure 1: Location of Court Houses

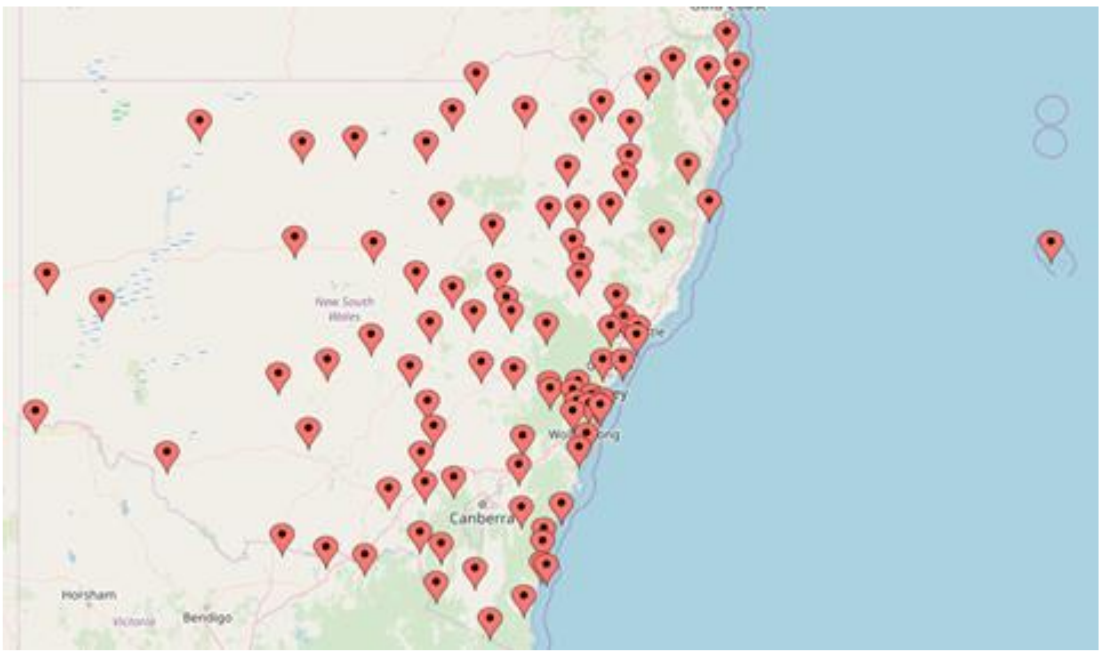


[3] District Courts hold trials and sentence hearings and can be judged alone or trialled by jury (District Court Act, 1973). Only a few District court cases each year go to a jury trial, with most court cases occurring in Local Courts with no jury (ABS, 2019). Sentence hearings are heard by an individual judge with no jury and are only held when a defendant pleads guilty.

B. Weather Data

Weather data were obtained from the Bureau of Meteorology. [4] Data are available for a total of 449 weather stations in NSW, including locations that are no longer operational or have incomplete observations. This paper utilises 97 of them from a range of locations, shown in Figure 2, selected due to availability of data between the focus dates of 1994 to 2019.

Figure 2: Location of Weather Stations (Excluding Norfolk Island)



We utilised station-day level weather data on temperature, rainfall and solar exposure. The main temperature variable used in the analysis is defined as the average of the daily minimum temperature and maximum temperature, which we converted to degrees Fahrenheit.[5] Rainfall and solar exposure are used as control variables, since they may be correlated with temperature and have been shown to influence cognitive ability (Allen and Fischer, 1978; Denissen et al, 2008).

Rainfall is measured in millimetres and it includes all forms of precipitation including snow. Daily weather data include rainfall observations for the 24 hour period up to 9am on a given day. We therefore match court cases with the rainfall observation recorded on the following day.

[4] Data available from www.bom.gov.au/climate/data/index.shtml

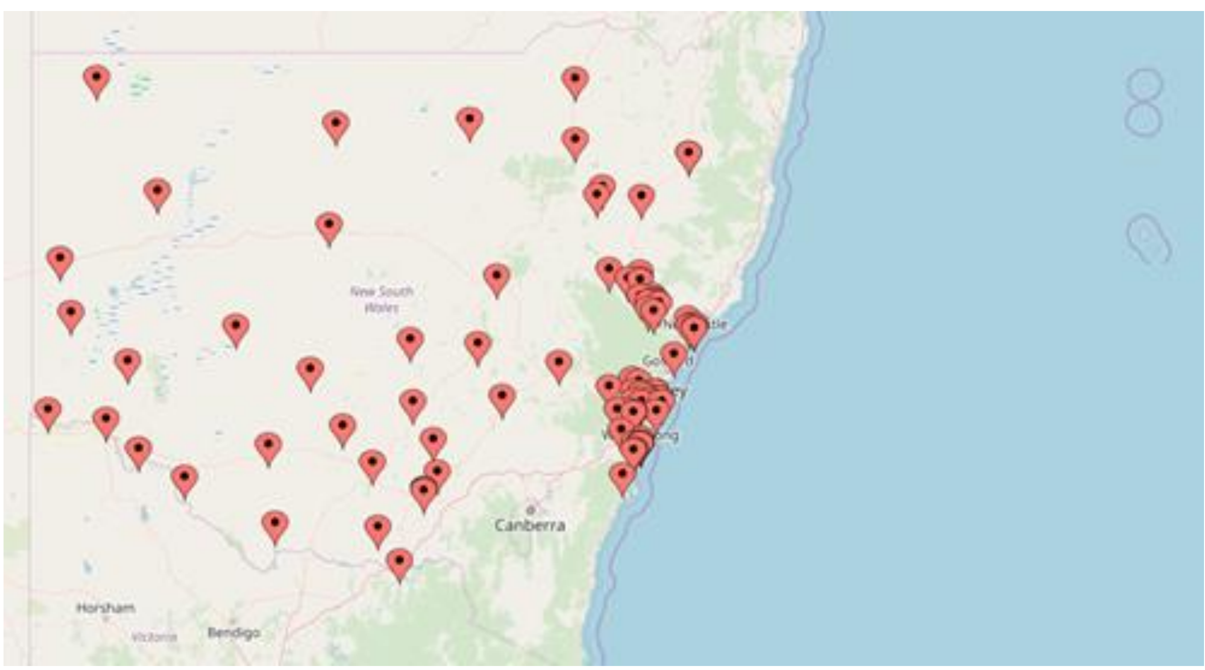
[5] Heyes and Saberian (2019) use average hourly temperature from 6am to 4pm in their preferred specification. They show that using average daily temperature instead leads to similar (although slightly attenuated) results.

The level of solar exposure is measured daily and is the total solar energy received in a day, measured in megajoules per square metre. These weather data are merged to cases heard at courts located within 30km. Where two or more active weather stations are located within 30km of a given court, we take a weighted average of the weather observations, with higher weights given to closer weather station.[6]

C. Pollution Data

Pollution data were sourced from the NSW Department of Planning, Industry and Environment formerly known as the Office of Environment and Heritage (OEH).[7] This dataset includes air-quality indicators of carbon monoxide (CO), ozone (O3) and particulate matter (PM2.5). The monitoring stations are all National Association of Testing Authorities (NATA) accredited. The 99 air-quality stations are located across the NSW region, with 43 of these locations holding data on carbon monoxide, ozone or particulate matter between 1994 and July 2019. Data were extracted as a daily average based on hourly data or 8-hour rolling averages. The locations of the air quality control stations are depicted in Figure 3.

Figure 3: Location of Air Quality Control Stations



[6] The weights are proportional to the inverse squared-distance between court and weather station.

[7] Data available from www.environment.nsw.gov.au/AQMS/search.htm

D. Descriptive Statistics

Table 1 presents summary statistics from the merged data set. As shown, 89% of cases were given guilty verdicts. There are missing pollution data for a large number of cases. For this reason, our main specification does not include pollution controls. However, we show that results are not sensitive to the inclusion of pollution controls.

Table 1: Summary Statistics

	Obs	**Mean**	**SD**	**Min**	**Max**
Temperature (°F)	2,817,711	64.08	9.15	28.49	103.64
Rainfall (mm)	2,787,311	3.77	10.97	0	293.6
Solar (MJ m^2)	2,678,396	17.09	7.74	0.1	35.7
CO	1,937,139	0.35	0.30	-0.3	4.1
Ozone	2,022,612	1.47	0.64	0	5.8
Particles	1,862,975	5.18	4.38	-1	311.1
Guilt Indicator	2,817,711	0.89	0.32	0	1

Notes: 'Guilt Indicator' is a dummy variable that takes the value one if sentence is guilty, zero otherwise

Amongst cases with a guilty verdict, the most frequently occurring penalty types are fines, imprisonment and bonds. Bonds can be supervised or unsupervised and can be elicited with or without a conviction.[8] Fines are measured in Australian dollars whilst bonds and imprisonments are both measured in months.

There is a large range of criminal cases included in the data. Table 2 shows the top ten most frequent crime types, and the proportion judged to be guilty. These crimes can also be grouped within a three-category classification: crimes against organisations, crimes against people and crimes against property (Australian Bureau of Statistics, 2011). Most of the crimes in our data are crimes against organisations, which includes traffic offences as well as drug possession.

[8] Bond includes the following categories "Bond without conviction without supervision", "Bond without supervision", "Bond with supervision", "Bond without conviction with supervision", "Community Correction Order with supervision", "Community Correction Order without supervision", "Conditional Release Order with conviction, without supervision", "Conditional Release Order with conviction, with supervision", "Conditional Release Order without conviction, without supervision" and "Conditional Release Order without conviction, with supervision". Due to legislative changes in 2018 (Crimes (Sentencing Procedure) Amendment (Sentencing Options) Act 2017 s.9), bonds have been replaced by Community Correction Orders and Conditional Release Orders.

Table 2: Distribution of Crime Type

	Obs	%	Guilt Indicator
Exceed Prescribed Content of Alcohol	448,199	15.91	0.99 [0.09]
Drive with Disqualified or Suspended License	222,084	7.88	0.95 [0.21]
Common Assault	214,899	7.63	0.78 [0.42]
Serious Assault Resulting in Injury	151,480	5.38	0.72 [0.45]
Possess Illicit Drugs	149,052	5.29	0.96 [0.19]
Drive Without a License	107,088	3.80	0.97 [0.17]
Dangerous or Negligent Operation of a Vehicle	94,596	3.36	0.84 [0.36]
Breach of Violence Order	92,529	3.28	0.80 [0.40]
Property Damage, Other	89,553	3.18	0.90 [0.30]
Theft (Except Motor Vehicles), Other	79,684	2.83	0.91 [0.29]

Notes: The top ten most frequently reported crimes in the data set. Percentage is displayed as the proportion of the data set as a whole. 'Guilt Indicator' is a dummy variable that takes the value one if sentence is guilty, zero otherwise. The standard deviations are listed in brackets next to the mean.

IV. Methods

The basic empirical strategy is to estimate linear probability regression models of the following form:

$$g_{ict} = \alpha + \beta_1 temp_{ct} + \beta_2 W_{ict} + \theta_t + \gamma_{ct} + \varepsilon_{ict} \qquad (1)$$

The dependent variable g_{ict}, is a dummy variable equal to one if the sentence for case i at court c, on finalisation date t is judged as 'guilty', and zero for all other outcomes, including 'mental health dismissal' and 'not guilty'. The constant is denoted α. β_1 is the coefficient of the key independent variable $temp_{ct}$, which in turn is the estimated average outdoor temperature on day t at court location c. W_{ict} denotes controls, which in the main model includes rainfall and solar exposure, and crime type indicators (125 different crime types). In robustness tests, it also includes pollution variables.

The model also contains a rich set of fixed effects. θ_t denotes day-of-week and year fixed effects, and γ_{ct} includes court location-by-month fixed effects. Following Heyes and Saberian (2019), we see this set of fixed effects as the most natural specification to account for spatial variation, time trends, and to flexibly account for seasonality. Conditional on these fixed effects and the controls, variation in temperature is plausibly random. We also show a variety of robustness tests, varying the control variables used, as well as the specification of fixed effects.

Standard errors are clustered on court location.

We also show results which consider the severity of punishment. In those models, we replace g_{ict} with alternate outcome variables. In some of these, we replace the dependent variable with $p_{it,}$, a dummy variable that depicts a particular penalty type (fine, bond, or imprisonment). Such models are estimated using the subset of cases judged as guilty. We also estimate models with continuous measures of severity, $s_{ict,}$, measured in months or dollars depending on the type of penalty. Those models are estimated on the subset of crimes judged as guilty, separately by type of penalty. In all of these alternate models, the independent variables and fixed effects are the same as in the main analysis.

V. Results

A. Main Results

Table 3 shows the main results as per equation (1). To reduce the number of decimal points and to aid interpretation, we specify temperature in degrees divided by 1000 in the regression (and similarly for the other weather variables).

Table 3: Main Results

	No Controls (1)		**Weather Controls (2)**		**Weather and Crime Type Controls (3)**	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Temperature/1000	0.0485 [0.0629]	0.443	0.0357 [0.0652]	0.585	0.0405 [0.0571]	0.479
Rainfall/1000	-	-	-0.0758* [0.0421]	0.074	-0.0558* [0.0288]	0.055
Solar Exposure/1000	-	-	0.0095 [0.0593]	0.873	-0.0113 [0.0496]	0.821
	95% Confidence Interval		95% Confidence Interval		95% Confidence Interval	
Temperature/1000	-0.0761	0.1731	-0.0933	0.1647	-0.0725	0.1535
Rainfall/1000	-	-	-0.1591	0.0075	-0.1129	0.0012
Solar Exposure/1000	-	-	-0.1079	0.1269	-0.1094	0.0869
Observations	2,817,702		2,652,386		2,652,386	

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. Rainfall is measured in millimetres and solar exposure is measured in megajoules per square metre. Standard errors are clustered on court location in brackets. The regression is run using day of week, year and court-month fixed effects. Values are rounded to four decimal places. Statistical significance is marked in the following ***p<0.01 **p<0.05 and *p<0.1. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

The results show no evidence of a relationship between temperature and court outcomes. The estimates in Table 3 are not only small but very precisely estimated. The 95% confidence intervals rule out even very small effects. To illustrate, the point estimates in each column suggest that a 10 degree increase in temperature is associated with a 0.036 to 0.049 percentage point higher probability of a guilty outcome. The 95% confidence intervals in the preferred specification (column 3) rule out effects greater than 0.15 percentage points associated with a 10 degree increase in temperature. The effect of rainfall is marginally significant (at the 10% level), and again very small. Taken at face-value, the point estimate in the preferred specification suggests that 10mm of rain would reduce the probability of a guilty verdict by 0.056 percentage points.

Table 4 shows results which use alternate temporal and spatial fixed effect bundles. This allows us to examine how alternate sources of identifying variation can affect the results.[9]

Table 4: Alternative Fixed Effects

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Temperature/1000	0.1832*	0.1857*	0.2094**	0.0110	0.3604***	-0.0555	0.0405
	[-0.0886]	[0.1022]	[0.0924]	[0.0461]	[0.0337]	[0.1203]	[0.0571]
p-value	0.078	0.072	0.025	0.812	0.000	0.645	0.479
Day of Week FE	N	Y	Y	Y	Y	N	Y
Court-Month FE	N	N	Y	N	N	Y	Y
Court FE	N	N	N	Y	Y	N	N
Year FE	N	N	N	N	Y	Y	Y
Year-Month FE	N	N	N	Y	N	N	N
Date FE	N	N	N	N	N	Y	N
Observations	2,652,395	2,652,395	2,652,386	2,652,395	2,652,395	2,651,678	2,652,386

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. The regressions control for daily rainfall (millimetres) and solar exposure (megajoules per square metre) and crime type indicators. Standard errors are clustered on court location in brackets. Values are rounded to four decimal places. Statistical significance is marked in the following ***p<0.01 **p<0.05 and *p<0.1. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

Column 7 shows results for the preferred specification (as per Table 3, column 3). The estimates in columns 4, 6 and 7 are not statistically significant. The estimates in columns 1 and 2 are marginally significant, but these specifications are almost completely devoid of fixed effects that are needed to control for unobserved characteristics of cases. The estimate in column 3 is

[9] The total number of observations varies depending on the fixed effects used, due to the removal of singleton observations.

significant at the 5% level. That specification includes day-of-week and court-month fixed effects, which control for location-specific seasonality. But this specification does not account for likely trends in sentencing decisions over time. The estimate in column 5 is also statistically significant. This specification includes day-of-week, court and year fixed effects, but it does not control for likely seasonal variation in the nature or severity of crime (even though type of crime is controlled for). Even the largest of these estimates (5) is arguably small (suggesting that a 10 degree increase in temperature is associated with a 0.36 percentage point higher probability of a guilty outcome) and much smaller than Heyes & Saberian's (2019) estimates for migration court decisions.

Temperature may affect the severity of sentencing, rather than the likelihood of a guilty outcome. We show results from models which consider severity in Table 5.

Table 5: Estimated Effects on Type and Severity of Sentence

	Fine **(1)**	**Bond** **(2)**	**Imprisonment** **(3)**
		A: Sentence Type	
Temperature/1000	0.0672	-0.0468	0.0197
(SE)	[0.1070]	[0.0806]	[0.0530]
p-value	0.531	0.562	0.711
Observations	1,072,715	719,850	210,325
		B: Severity of Sentence	
Mean	530.74	15.59	17.78
SD	903.12	7.54	27.64
Temperature	0.3703	-0.0028	0.0127
(SE)	[0.3917]	[0.0056]	[0.0163]
p-value	0.346	0.625	0.438
Observations	1,000,552	685,190	199,365

Notes: Panel A: The sample is restricted to cases with a guilty verdict. The dependent variable is a dummy variable indicating the sentence type, taking the value one if the type matches the named variable in the column. The regressions control for daily rainfall (millimetres), solar exposure (megajoules per square metre) and crime type indicators. Panel B: The sample is restricted to cases with a guilty verdict and a particular sentence type. The dependent variable is a measure of the severity of punishment. The regressions control for daily rainfall (millimetres) and solar exposure (megajoules per square metre). The Table 5 regressions do not control for crime-type indicators because this introduces singularities into the standard error calculations for column 1. However the corresponding point estimates are very similar when crime type indicators are included. Fine is measured in Australian dollars. Bond is measured in the number of months, unless otherwise stated. Imprisonment is measured in months, unless otherwise stated. In Panel B column 1 contains 119 clusters, column 2 contains 120 clusters and column 3 contains 114 clusters. Throughout the table, temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. Temperature is divided by 1000 in Panel A, but not in Panel B, reflecting the scale of the outcome variables. These regressions include day of week, year and court-month fixed effects. Standard errors are clustered on court location in brackets. Values are rounded to four decimal places. Statistical significance is marked in the following ***p<0.01 **p<0.05 and *p<0.1. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

Panel A shows results estimated on a sample which is restricted to cases with a guilty verdict. The dependent variable is a dummy variable indicating whether the penalty was a fine, bond or an imprisonment, respectively. Panel B shows results where each dependent variable is a quantitative measure of the size of the penalty. In each column, the sample is restricted to cases with a guilty verdict and a particular sentence type. The dependent variable is measured as a dollar amount for fines, and months for bonds and imprisonment. None of the estimates in this table are statistically significant. All point-estimates are economically small: in Panel A, the largest point estimate implies a 0.07 percentage point effect associated with a 10 degree increase in temperature; while the largest estimated effect in Panel B implies a 0.7% effect relative to the mean.

B. Sub-Group Analysis

The court data span 125 types of crimes of varying degrees of severity. The type of crime or its severity may influence the likelihood that a judge or magistrate is influenced by temperature. Table 6 shows estimates for each of the ten most frequent offences. The estimates are not statistically significant at the 10% level for any of these offences, and all are small. Many have negative signs.

To investigate this further, Table 7 shows estimates for each of the sixteen divisions of crimes, (Australian Bureau of Statistics, 2011). All but one of the estimates are statistically insignificant at the 10% level. The exception is ‘Theft’, for which the estimate is statistically significant with a p-value of 0.068. Given the many hypotheses being tested here, it is not appropriate to interpret this as convincing evidence of an effect for Theft, and in any case the estimate is small.

Table 6: Estimated Effects by Type of Crimes

	(1) Exceed Prescribed Content Alcohol	**(2) Drive with Disqualified/ Suspended License**	**(3) Common Assault**	**(4) Serious Assault Resulting in Injury**	**(5) Possess Illicit Drugs**	**(6) Drive Without License**	**(7) Dangerous/ Negligent Operation of Vehicle**	**(8) Breach of Violence Order**	**(9) Property Damage, Other**	**(10) Theft, Other**
Temperature/	-0.0584	0.1242	0.1089	-0.0750	-0.0925	-0.1265	-0.4480	-0.0884	-0.1495	0.1273
1000	[0.0365]	[0.1112]	[0.2058]	[0.2603]	[0.1108]	[0.1187]	[0.2757]	[0.2282]	[0.2547]	[0.2639]
p-value	0.112	0.266	0.598	0.774	0.406	0.289	0.107	0.699	0.558	0.630
Observations	420,842	212,371	200,004	143,514	143,056	102,400	88,386	87,366	83,207	72,597

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. The regressions control for daily rainfall (millimetres) and solar exposure (megajoules per square metre). These regressions include day of week, year and court-month fixed effects. Standard errors are clustered on court location in brackets. Values are rounded to four decimal places. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

Table 7: Estimated Effects by ANZSOC Division

Category	Observations	Temperature/1000	*p*-value
01 Homicide	4,679	-1.4079	0.249
		[1.2103]	
02 Injury	434,474	0.0331	0.809
		[0.1365]	
03 Sexual Assault	28,070	-0.1526	0.837
		[0.7413]	
04 Dangerous/ Negligent	107,286	-0.2550	0.314
		[0.2522]	
05 Abduction/ Harassment	14,515	-0.7948	0.226
		[0.6528]	
06 Robbery	27,642	0.0741	0.893
		[0.5473]	
07 Unlawful Entry	65,238	0.4684	0.197
		[0.3611]	
08 Theft	243,760	0.2949*	0.068
		[0.1600]	
09 Fraud/ Deception	84,139	0.0138	0.946
		[0.2046]	
10 Illicit Drugs	209,257	0.0614	0.686
		[0.1515]	
11 Weapons	34,984	0.2094	0.617
		[0.4177]	
12 Property/ Environment	94,990	-0.2247	0.367
		[0.2483]	
13 Public Order Offences	139,396	0.2778	0.292
		[0.2622]	
14 Traffic/ Vehicle	856,595	-0.0146	0.732
		[0.0427]	
15 Offence Against Justice	266,123	-0.0079	0.956
		[0.1441]	
16 Miscellaneous	39,987	0.4764	0.404
		[0.5685]	

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. The regressions are controlled for daily rainfall (millimetres) and solar exposure (megajoules per square metre). These regressions include day of week, year and court-month fixed effects. Standard errors are clustered on court location in brackets. Values are rounded to four decimal places. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

Next, these divisions can be categorised as crimes against people, crimes against property or crimes against institutions. None of these estimates are significant at the 5% level, as shown in Table 8. The estimate for 'Crimes against property' (the smallest of these categories) is however marginally significant at the 10% level.

Table 8: Estimated Effects by ANZSOC Category

Category	**Observations**	**Temperature /1000**	***p*-value**
Crimes Against People	617,457	-0.0505	0.666
		[0.1166]	
Crimes Against Property	516,100	0.1555*	0.075
		[0.0867]	
Crimes Against Organisation	1,546,575	0.0493	0.468
		[0.0677]	

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. The regressions control for daily rainfall (millimetres) and solar exposure (megajoules per square metre). Crimes against people includes divisions 01 to 06. Crimes against property includes divisions 06 to 09 and 12. Crimes against organisations includes divisions 10 to 11 and 13 to 16. These regressions include day of week, year and court-month fixed effects. Standard errors are clustered on court location in brackets. Values are rounded to four decimal places. Statistical significance is marked in the following ***p<0.01 **p<0.05 and *p<0.1. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

Table 9 shows results by region of court, using the preferred specification.[10] None of these estimates are significant at the 10% level.

Table 10 shows results for various year groups, using the preferred specification. One motivation for this analysis is that air conditioning may have become more common in recent years, potentially reducing the influence of outdoor temperature. However, the results do not support this hypothesis. None of the estimates are statistically significant at the 5% level and there is no apparent pattern in the estimates over time.

C. Pollution Controls

A priori, we planned for our specification to control for pollution. Doing so would also produce more directly comparable results to Heyes and Saberian (2019). Including these controls, however, reduces the estimation sample by 35% since pollution data is relatively sparse geographically. Nevertheless, we show results in this sub-section which suggest that the results are not sensitive to the inclusion of pollution controls.

[10] The classification of regions has five categories: Major Cities, Inner Regional, Outer Regional, Remote and Very Remote (ABS, 2018). Due to few observations in 'Very Remote' areas, these are not shown separately, but are included in the Rural category.

Table 9: Estimated Effects by Region

	Obs	**Temperature/1000**	**SE**	***p*-value**	**95 % Confidence Interval**	
Major Cities	2,069,195	0.0489	0.0666	0.467	-0.0850	0.1828
Inner Regional	428,576	0.0611	0.1183	0.609	-0.1790	0.3012
Outer Regional	122,964	-0.1668	0.1205	0.179	-0.4150	0.0814
Remote	28,399	-0.1048	0.5098	0.843	-1.3103	1.1008
Urban	2,497,771	0.0543	0.0602	0.369	-0.0653	0.1740
Rural	154,615	-0.1009	0.1397	0.475	-0.3849	0.1831

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. The regressions control for daily rainfall (millimetres) and solar exposure (megajoules per square metre) and crime type indicators. Standard errors are clustered on court location in brackets. Results for 'Very Remote' areas are not shown separately due to insufficient observations. Urban includes 'Major Cities' and 'Inner Regional' and rural includes 'Outer Regional', 'Remote' and 'Very Remote'. The regressions include day of week, year and court-month fixed effects. Values are rounded to four decimal places. Statistical significance is marked in the following ***p<0.01 **p<0.05 and *p<0.1. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

Table 10: Estimated Effects by Year

	(1) 1994-2000	**(2) 2001-2006**	**(3) 2007-2012**	**(4) 2013-2019**
Temperature/1000	-0.0848	0.0934	0.2151*	-0.0028
	[0.0902]	[0.1129]	[0.1230]	[0.0793]
p-value	0.349	0.410	0.083	0.972
Observations	557,917	646,516	689,952	757,987

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. 2019 incudes observations up to 31st July 2019. The regressions control for daily rainfall (millimetres), solar exposure (megajoules per square metre) and crime type indicators. These regressions include day of week, year and court-month fixed effects. Standard errors are clustered on court location in brackets. Values are rounded to four decimal places. Statistical significance is marked in the following ***p<0.01 **p<0.05 and *p<0.1. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

Column 1 in Table 11 shows the regression output with pollution controls added to the preferred specification. This vector of controls includes carbon monoxide, ozone and particulates. The reported estimate for the effect of temperature is 0.0547, and is not statistically significant.

Column 2 shows results which instead use the main specification, but estimated on the same restricted sample as column 1. A comparison of the two columns shows that the results are very similar. Controlling for pollution increases the estimated effect of temperature slightly, by a magnitude equal to 30% of one standard error of the estimate. This strongly suggests that the main results are unlikely to be biased-downward by omitted pollution controls.

Table 11: Regression Output on Pollution Sample

	(1) Pollution Controls		**(2) No Pollution Controls**	
	Coefficient	***p*-value**	**Coefficient**	***p*-value**
Temperature/1000	0.0436	0.635	0.0191	0.816
	[0.0912]		[0.0816]	
Rainfall/1000	-0.0986*	0.063	-0.1001**	0.045
	[0.0519		[0.0486]	
Solar Exposure/1000	0.0173	0.821	0.0106	0.889
	[0.0761]		[0.0755]	
Carbon Monoxide/1000	-3.8473	0.135	-	-
	[2.5298]			
Ozone/1000	-0.7167	0.534	-	-
	[1.1435]			
Particulate/1000	0.0895	0.601	-	-
	[0.1670]			
Observations	1,721,458		1,721,458	

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. The regressions control for weather variables in the form of daily rainfall (millimetres) and solar exposure (megajoules per square metre), and crime type indicators. Standard errors are clustered on court location, in brackets (resulting in 49 clusters). Values are rounded to four decimal places. Source for court data: NSW Bureau of Crime Statistics and Research: <rod18010ac 2019>.

D. *Nonlinear effects*

We now test for nonlinear effects of temperature, first by including a quadratic function of temperature, and then non-parametrically, using 10-degree temperature bins. The results are shown in Table 12.

Panel A shows no evidence of nonlinear effects. In each column, temperature-squared is not statically significant, nor are the two temperature variables jointly significant.

Table 12: Estimated Nonlinear Effects of Temperature

	No Controls		Weather Controls		Crime Type Controls	
	Coef	***p*-value**	**Coef**	***p*-value**	**Coef**	***p*-value**
			A: Quadratic in Temperature			
Temp/1000	-0.0878	0.855	0.1133	0.796	-0.0990	0.809
	[0.4803]		[0.4371]		[0.4087]	
Temp^2/1000	0.0010	0.773	-0.0006	0.857	0.0011	0.726
	[0.0036]		[0.0033]		[0.0030]	
p-value for joint significance		0.6966		0.8494		0.7001
			B: Temperature Bins			
Temp < 45	1.5220	0.575	2.0916	0.453	2.6162	0.287
	[2.7045]		[2.7781]		[2.4470]	
45 <= Temp < 55	-0.3715	0.716	-0.5508	0.545	-0.0204	0.981
	[1.0170]		[0.9068]		[0.8482]	
65 <= Temp < 75	-0.3237	0.731	-0.4329	0.678	-0.0276	0.978
	[0.9401]		[1.0386]		[1.0033]	
Temp >= 75	-0.8052	0.519	-1.3861	0.273	-0.8215	0.454
	[1.2443]		[1.2596]		[1.0932]	
p-value for joint significance		0.8788		0.6164		0.6489

Notes: The dependent variable is a dummy variable indicating a guilty sentence. Temperature is the average of the minimum and maximum temperature of a day measured in degrees Fahrenheit. The regressions control for weather variables in the form of daily rainfall (millimetres) and solar exposure (megajoules per square metre), and crime type indicators. Standard errors are clustered on court location in brackets. The regression is run using day of week, year and court-month fixed effects. Values are rounded to four decimal places. Statistical significance is marked in the following ***p<0.01 **p<0.05 and *p<0.1.

Panel B shows the effects of temperature in 10-degree bins. Here, the temperature categories are not jointly significant in each column, nor individually.

VI. Conclusion

We have found no evidence that transient variations in temperature affect the outcomes of criminal court cases in the state of New South Wales, despite using data on 2.8 Million cases. The main estimates are not statistically significant, but they are precise, in the sense that the standard errors are very small. The point estimates suggest that even an increase of 10°F raises the probability of a guilty sentence by only 0.04 percentage points. The 95% Confidence Interval rules out effects larger than 0.15 percentage points associated with a 10°F increase in temperature. We also find no evidence that temperature affects the severity of sentencing. Subgroup analysis shows little evidence of significant effects for any subset of crimes, or over any time period or any region. The significant effects we find for sub-groups are always small and would not survive any adjustment for multiple hypothesis testing. We have also found no evidence of nonlinear effects of temperature, using parametric and non-parametric specifications.

These results are reassuring for the integrity of judge decision-making in criminal court cases. They contrast with earlier work which has found evidence that judges and magistrates respond to idiosyncratic external factors irrelevant to the case at hand (Englich et al., 2006; Danziger et al., 2011; Eren and Mocan, 2018; Heyes & Saberian, 2019; Chen and Loecher, 2020). Any assessment of the likely overall importance of such idiosyncratic factors on court decisions should expect that studies such as ours are less likely to be visible, due to issues of publication bias. Efforts to address publication bias and to promote replication work is an important development towards improving the scientific validity of empirical work on this and many other topics.

Further research on this topic would be worthwhile to explore external validity. Such work could focus on places with different legal systems, different climates, or different building standards (which could reflect the relationship between the outdoor and indoor climates). Further work may also consider other ways of inferring decision quality. As acknowledged by (Heyes and Saberian, 2019), a relationship between temperature and the probability of a favourable outcome says nothing about whether hot or cold weather lead to better decision making.

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