Online appendix

Understanding the Link between Temperature and Crime

Francois Cohen and Fidel Gonzalez

We provide nine online appendices:

A – Summary statistics

B – Additional analyses on the association between the weather and crime

C – Robustness checks on short-terms dynamics

D – Additional tests for sample selection

E – Complementary analyses for the impact of the weather on time use

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H – Additional results on the interaction between the weather, temperature, and crime

I – Robustness checks to understand better the effect of weekends on crime

A: Summary statistics

The table below provides summary statistics from administrative records of the Criminal Courts of First Instance (*Juzgados Penales de Primera Instancia*), and the daily temperature and precipitation data from the National Climatological Database of Mexico (CONAGUA, 2021).

Table A1. Summary statistics

Panel A: Crime statistics

Crime category	Average daily charge rate	Crime category	Average daily charge rate
All crimes	5.75	Male offenders	10.91
Homicide	0.20	Female offenders	1.12
Injury	0.88	Offenders aged under 25	9.27
Sexual crime	0.25	Offenders aged 25-65	9.04
Family violence	0.09	Offenders aged over 65	1.47
Theft	1.71	Offender is prosecuted	4.16
Fraud	0.11	Offender is convicted	3.65
Property damage	0.48	Unintentional crimes	0.53
Kidnapping	0.06	Failed attempts	0.18
Weapon-related crime	0.47	Offenders in normal state	4.52
Drug-related crime	0.42	Drunk offenders	0.81
Concerted crime	0.08	Charge rate on weekends	5.61
All other crimes	1.00	Charge rate on weekdays	6.12

Panel B: Weather statistics

Temperature bins	Av. no. of days per year	Temperature bins	Av. no. of days per year
<10°C	5.44	22-24°C	32.74
10-12°C	12.78	24-16°C	28.22
12-14°C	27.61	26-28°C	29.05
14-16°C	44.03	28-30°C	22.06
16-18°C	59.03	30-32°C	7.94
18-20°C	51.09	>32°C	2.49
20-22°C	42.78		

Precipitation bins	Av. no. of days per year	Precipitation bins	Av. no. of days per year
0 mm	219.17	10-15 mm	11.83
0-5 mm	91.33	15-20 mm	6.12
5-10 mm	25.16	>20 mm	11.64

Variable	Mean	Standard deviation
Average daily temperature	19.91	5.32
Total daily precipitations	2.55	7.32

Notes: Statistics are weighted by the population in each municipality and category. The figures are averages in the matched dataset but may differ from the sample average used in specific regressions. In Panel A, the charge rates correspond to the average daily charge per million inhabitants at the municipality level. Statistics by gender and age group are divided by the population in each corresponding group. The sum of offenses conducted by offenders in normal state and drunk offenders do not add up to the charge rate for all crimes because this information is not reported on all crimes and they also represent a very small share of all crimes. Also, there were 0.8 percent of missing values for temperature in our data. Therefore, the sum of the number of days falling in any temperature bins added up to around 362 instead of 365.25 per year, with 3.25 days per year recording missing values. **Table A1** corrects for this and displays results for 365.25 days per year.

B: Additional analyses on the association between the weather and crime

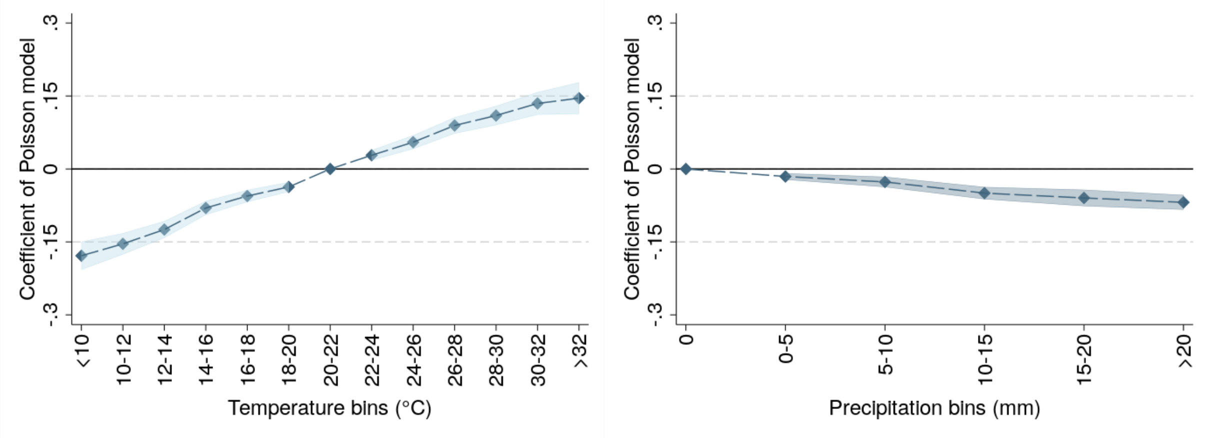
In **Appendix B.1**, instead of using linear models, we run fixed effect Poisson regressions to account for the present of zero values in the dependent variable. Results with Poisson models are very similar to those displayed on **Figure 1 and 2**. We also consider a few heterogeneous effects of temperature on crime. In **Appendix B.2**, we find that the temperature–crime relationship has been relatively stable over time even before and after the renewal of the Mexican war on drugs in 2006. We also show that the temperature-crime relationship is similar for rural and urban areas. In **Appendix B.3**, we also break down the correlation between temperature and crime by the gender and age of suspected offenders. The great majority of temperature-induced crime is performed by offenders below 65. In relative terms, we find that younger offenders are as sensitive to temperature as older offenders. We also show the results by age and gender focusing on comfortable temperatures between 18°C and 23°C. Results are very similar suggesting that extreme temperatures are not driving these results. In **Appendix B.4**, using the daily charges data, we also investigate whether impacts come from low minimum temperatures and/or high maximum temperatures. The results suggest that both minimum and maximum temperatures have an impact on the charge rate. In **Appendix B.5**, we provide results for agricultural workers since the agricultural channel has been identified as a mechanism behind the long-term correlation between temperature and violence. Our results show that agricultural workers spend more of their time outdoors, suggesting that they might also respond more to short-term temperature exposure. However, our results also suggest that the proportion of agricultural workers being suspected of a criminal offense is stable across the temperature range. Likewise, we find no correlation between rainfall and the share of crimes committed by agricultural workers. In **Appendix B.6**, we also consider the heterogeneity in the response of criminal charges to temperature in Mexico according to the diffusion of air-conditioning. We do not find differences in the association between temperature and crime according to the diffusion of air conditioning. However, these results could be confounded by other differences across Mexican States apart from different levels of AC penetration.

B.1. Results for all charges and by type of crime with a Poisson model

Our baseline results for **Figures 1 and 2** are based on linear models. These models can inefficiently estimate the association between temperature and the charge rate because charges are relatively rare events. Therefore, in some municipalities, there are many days with no charges. Overall, when we consder the number of daily charges per municipality, about 49 percent of the population-weighted daily observations have a zero value.

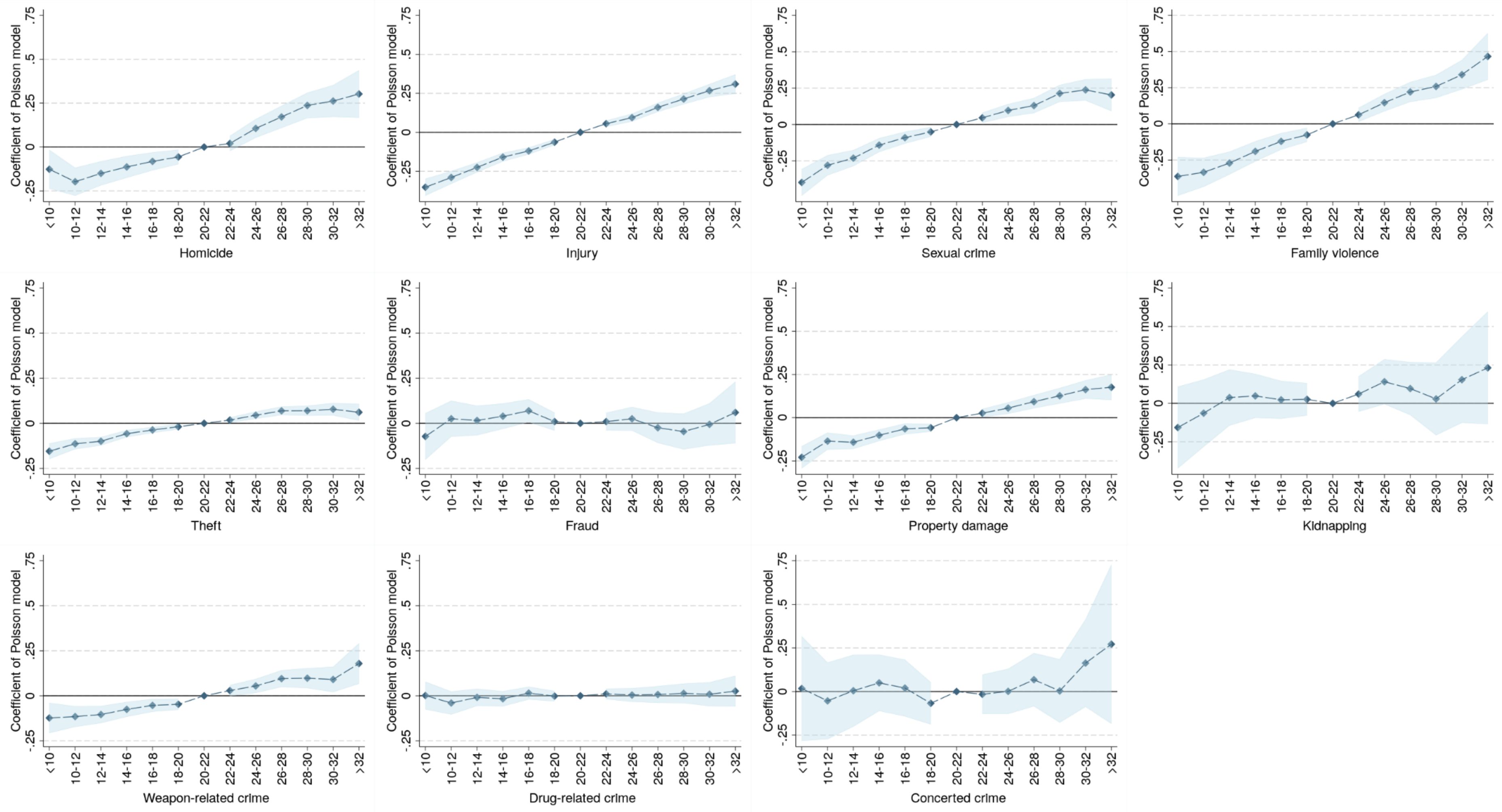
Fixed effect Poisson regressions are often used to increase the precision of estimates when the dependent variable includes many zero values. Below, we run fixed effect Poisson regressions where the dependent variables are the total number of charges in municipality *i* on day *d*, of month *m* and year *t*, for all charges and by type of crime. We furthermore include municipality by month and by year fixed effects and use robust standard errors. We then include the same temperature and precipitation bins as in **Figures 1 and 2**. Results with these non-linear specifications are very similar to the ones displayed on **Figures 1 and 2**.

Figure B1. Poisson model for the correlation between on-the-day temperature and daily charges



Notes: Both graphs present the results from the same Poisson regression. The dependent variable is the daily number of charges in each category. The independent variables are all the temperature bins listed on the x-axis of the panel on the left, and five (six minus the reference) precipitation bins, reported on x-axis of the right-hand panel. The regression includes municipality by month by year fixed effects. The solid line corresponds to the point estimates, while the shaded area corresponds to the 95% confidence intervals. We use robust standard errors, corrected to account for clusters at the municipal by month and by year level. The reference bin is 20–22°C for temperature and 0mm for precipitation.

Figure B2. Poisson model for the correlation between on-the-day temperature and daily charges by type of crime

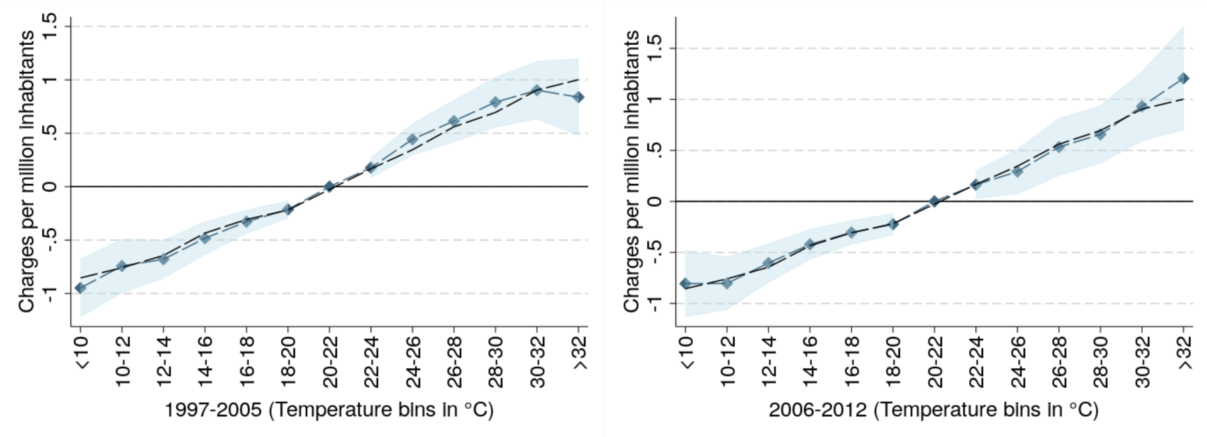


Notes: Each graph corresponds to a separate regression. The dependent variable is the daily number of charges in each category. The independent variables are all the temperature bins listed on the x-axis and five (six minus the reference) and precipitation bins (not reported in the graphs). Regressions include municipality by month by year fixed effects. The solid line corresponds to the point estimates, while the shaded area corresponds to the 95% confidence intervals. We use robust standard errors, corrected to account for clusters at the municipal by month and by year level. The reference bin is 20–22°C for temperature and 0mm for precipitations.

B.2. Separating the sample in two periods, and by rural/urban areas

The graphs in **Figure B3** below show the results from our baseline model for two periods: 1997-2005 and 2006-2012. Results are very similar, suggesting that the temperature-crime relationship has not evolved substantially over time.

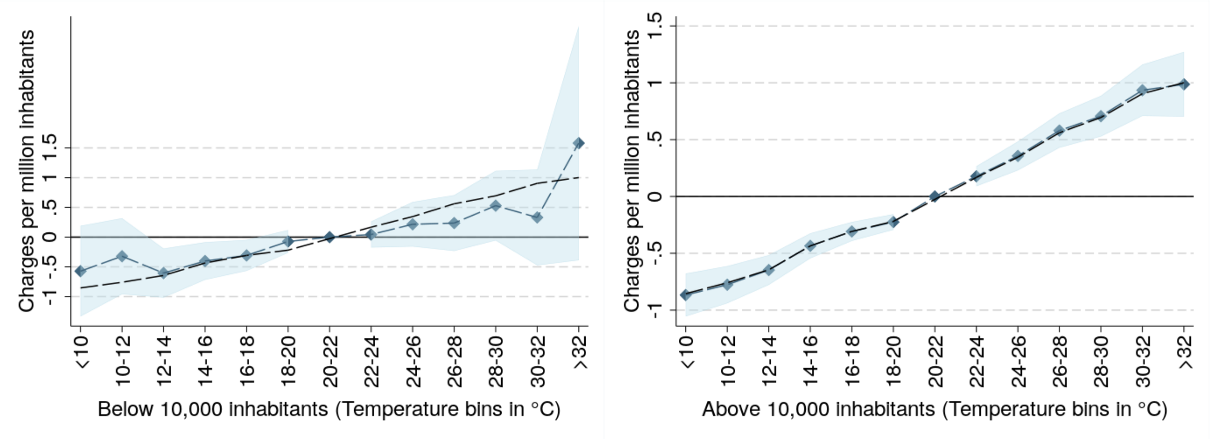
Figure B3. Correlation between temperature and the charge rate (for all types of crimes) before and after 2006



Notes: The panels correspond to the results of different specifications, corresponding to periods reported below each graph (1997-2005 on the left, and 2006-2012 on the right). In all panels, the dependent variable measured in the y-axis is the daily charge rate (all crimes) in crimes per million inhabitants. We report the results for all the temperature bins (on the x-axis). Regressions include date fixed effects (day, month and year), municipality by month and year fixed effects, and municipality by calendar day fixed effects. They also include the precipitation bins used in the baseline model. Observations are weighted by the population in each municipality. The solid line corresponds to the point estimates, while the 95% confidence intervals are indicated by the shaded areas for standard errors clustered at the municipality level. For comparison, the dashed lines correspond to the point estimates of the baseline model of Figure 1. The reference bin is 20-22°C for temperature, and 0mm for precipitation.

In **Figure B4**, we separate results for municipalities with less than 10,000 inhabitants and municipalities with more than 10,000 inhabitants are reported below. They are imprecise for municipalities with less than 10,000 inhabitants, but suggest that temperature and crime correlate as in the baseline specification.

Figure B4. Correlation between temperature and the charge rate (for all types of crimes) in municipalities with less or more than 10,000 inhabitants



Notes: The panels correspond to the results of different specifications, corresponding to municipality samples reported below each graph (those with less than 10,000 inhabitants on the left, and those with more than 10,000 inhabitants on the right). In all panels, the dependent variable measured in the y-axis is the daily charge rate (all crimes) in crimes per million inhabitants. We report the results for all the temperature bins (on the x-axis). Regressions include date fixed effects (day, month and year), municipality by month and year fixed effects, and municipality by calendar day fixed effects. They also include the precipitation bins used in the baseline model. Observations are weighted by the population in each municipality. The solid line corresponds to the point estimates, while the 95% confidence intervals are indicated by the shaded areas for standard errors clustered at the municipality level. For comparison, the dashed lines correspond to the point estimates of the baseline model of Figure 1. The reference bin is 20-22°C for temperature, and 0mm for precipitation.

B.3. Results by age and gender

Table B1. Effect of one °C on the charge rate by gender and age of offenders

	Gender of offenders		Age of offenders		
	Male	Female	<25	25-65	>65
In charges per million people:					
All crimes	0.197***	0.0148***	0.16***	0.162***	0.0266***
	(0.0125)	(0.0028)	(0.0139)	(0.0119)	(0.0087)
As a share of average rate in estimation sample:					
All crimes	1.81%***	1.32%***	1.73%***	1.8%***	1.82%***
	(0.11%)	(0.25%)	(0.15%)	(0.13%)	(0.59%)
Homicide	2.63%***	1.48%	3.09%***	2.53%***	-0.34%
	(0.4%)	(1.22%)	(0.65%)	(0.45%)	(2.46%)
Injury	3.17%***	2.12%***	3.69%***	2.8%***	3.32%***
	(0.26%)	(0.4%)	(0.38%)	(0.26%)	(1.01%)
Sexual crime	2.46%***	0.42%	2.07%***	2.74%***	0.42%
	(0.33%)	(1.86%)	(0.53%)	(0.41%)	(1.71%)
Family violence	4.32%***	4.65%***	3.19%***	4.5%***	7.73%**
	(0.55%)	(1.42%)	(0.93%)	(0.61%)	(3.63%)
Theft	1.18%***	0.73%**	1.2%***	1.11%***	1.41%
	(0.13%)	(0.34%)	(0.16%)	(0.16%)	(1.57%)
Fraud	0.25%	-0.38%	-0.38%	0.13%	-0.19%
	(0.46%)	(0.74%)	(1.64%)	(0.45%)	(1.86%)
Property damage	2.23%***	1.96%***	2.89%***	2.03%***	1.96%
	(0.29%)	(0.63%)	(0.45%)	(0.31%)	(1.65%)
Kidnapping	1.73%**	3.53%**	1.15%	2.51%***	7.4%
	(0.88%)	(1.69%)	(1.32%)	(0.91%)	(6.92%)
Weapon-related crime	1.86%***	-2.19%	1.38%**	1.96%***	2.43%*
	(0.48%)	(1.57%)	(0.56%)	(0.7%)	(1.43%)
Drug-related crime	0.2%	0.14%	0.22%	0.24%	0.72%
	(0.34%)	(0.94%)	(0.51%)	(0.33%)	(2.55%)
Concerted crime	1.01%	-0.04%	0.23%	1.2%	10.78%*
	(1.1%)	(2.59%)	(1.36%)	(1.31%)	(6.27%)
All other crimes	1.91%***	1.63%***	1.21%**	2.15%***	1.53%
	(0.25%)	(0.51%)	(0.5%)	(0.27%)	(0.96%)

Notes: Results come from separate regressions and display the effect obtained for daily temperatures (in °C). The dependent variable corresponds to the crime type described in the first column and for five demographic groups (male and female offenders, and offenders under 25, 25-65 and above 65). Results are expressed in charges per million people first, and then as a share of the estimation sample average, to allow for comparisons across demographic groups. Regressions include municipality by calendar day fixed effects, municipality by month by year fixed effects and exact date fixed effects (for each day, month and year). They also include daily precipitation (in mm) as control variable and are weighted by the population in each demographic group. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

Table B2 shows the result from **Table B1** but considering only comfortable temperatures between 18 and 23°C. Results are very similar suggesting that temperature extremes, or sample selection at unusual temperatures, are not driving these results by age and gender.

Table B2. Effect of one °C temperature temperature on the charge rate by gender and age of offenders at comfortable temperatures (18 to 23°C)

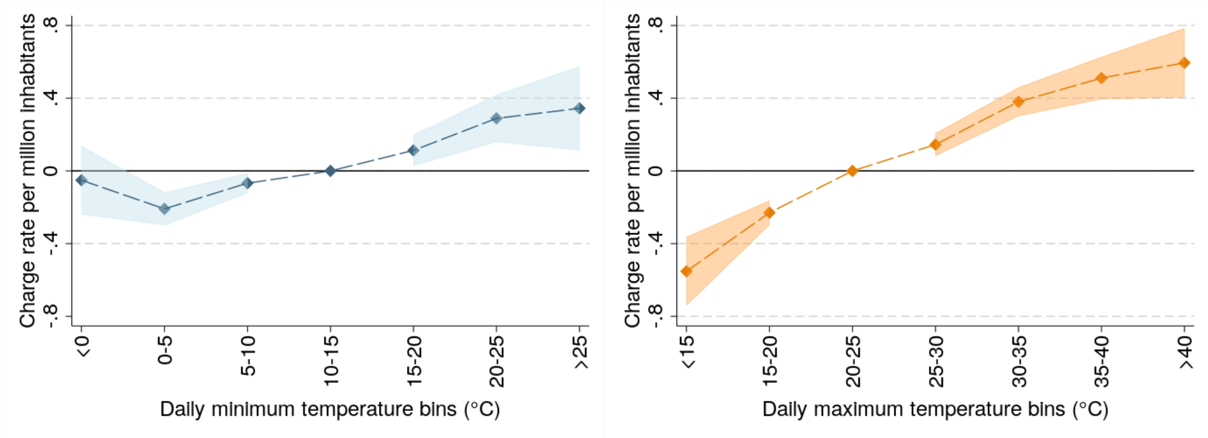
	Gender of offenders		Age of offenders		
	Male	Female	<25	25-65	>65
In charges per million people:					
All crimes	0.227***	0.0173**	0.18***	0.185***	0.0329
	(0.0298)	(0.0071)	(0.0397)	(0.0274)	(0.0249)
As a share of average rate in estimation sample:					
All crimes	2.04%***	1.49%**	1.89%***	2%***	2.17%
	(0.27%)	(0.61%)	(0.42%)	(0.3%)	(1.64%)
Homicide	2.92%**	-6.98%**	2.14%	2.72%*	-2.93%
	(1.15%)	(3.53%)	(1.7%)	(1.39%)	(7.87%)
Injury	3.22%***	1.24%	3.62%***	2.53%***	1.23%
	(0.54%)	(1.19%)	(0.82%)	(0.61%)	(3.13%)
Sexual crime	2.29%**	0.5%	5.84%***	1.27%	4.31%
	(0.93%)	(5.69%)	(1.46%)	(1.15%)	(4.9%)
Family violence	4.3%***	-0.15%	2.36%	3.99%***	18.38%
	(1.24%)	(4.24%)	(3.2%)	(1.44%)	(12.72%)
Theft	1.33%***	1.02%	1.36%**	1.23%***	2.56%
	(0.46%)	(1.23%)	(0.61%)	(0.47%)	(4.71%)
Fraud	2.45%*	1.26%	2.34%	2.33%*	2.24%
	(1.28%)	(2.72%)	(5.37%)	(1.3%)	(5.99%)
Property damage	2.2%***	2.95%	1.67%	2.25%***	5.69%
	(0.57%)	(1.87%)	(1.04%)	(0.64%)	(3.97%)
Kidnapping	1.01%	3.72%	1.74%	0.59%	31.86%*
	(2.89%)	(4.88%)	(4.79%)	(2.84%)	(17.49%)
Weapon-related crime	1.38%*	4.7%	1.19%	1.02%	2.56%
	(0.78%)	(4.54%)	(1.47%)	(1.03%)	(3.76%)
Drug-related crime	0.83%	2.33%	1.6%	0.87%	3.79%
	(1.05%)	(2%)	(1.54%)	(1.14%)	(6.34%)
Concerted crime	1.04%	7.93%	2.36%	-0.02%	36.46%
	(3.3%)	(6.31%)	(4.62%)	(3.5%)	(23.4%)
All other crimes	2.91%***	1.57%	0.86%	3.6%***	-0.91%
	(0.7%)	(1.4%)	(1.19%)	(0.67%)	(3.13%)

Notes: Sample is reduced to days with a temperature between 18 and 23°C. Results come from separate regressions and display the effect obtained for daily temperatures (°C). The dependent variable corresponds to the crime type described in the first column and for five demographic groups (male and female offenders, and offenders under 25, 25-65 and above 65). Results are expressed in charges per million people first, and then as a share of the estimation sample average, to allow for comparisons across demographic groups. Regressions include municipality by calendar day fixed effects, municipality by month by year fixed effects and exact date fixed effects (for each day, month and year). They also include daily precipitation (mm) as control variable and are weighted by the population in each demographic group. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

B.4. Results for daily minimum and maximum temperatures separately

We run our baseline model of **Figure 2** with two sets of temperature bins for minimum temperatures (<0; 0-5; 5-10; 10-15; 15-20; 20-25; and >25°C) and maximum temperatures (<15; 15-20; 20-25; 25-30; 30-35; 35-40; and >40°C). The regression includes both sets at the same time to estimate separately the effect of maximum and minimum temperatures. The results are shown in **Figure B5**.

Figure B5. Separate impact of minimum and maximum temperatures on the charge rate



Notes: The two panels are obtained from the same regression, with results for the coefficients for minimum temperature bins on the left and maximum temperature bins on the right panel. The dependent variable measured in the y-axis is the daily charge rate (all crimes) in crimes per million inhabitants. Regressions include municipality by calendar day (1-365) fixed effects, municipality by month by year fixed effects and a date fixed effect (day-month-year). Observations are weighted by the population in each municipality, as well as precipitation bins. The solid line corresponds to the point estimates, while the 95% confidence intervals are indicated by the shaded areas for standard errors clustered at the level of municipalities. The reference bin is 10-15°C for minimum temperature, 20-25°C for maximum temperature, and 0mm for precipitation.

B.5. Share of agricultural workers committing a crime

In **Table B3**, we show the regression results of the correlation between average daily temperature and the share of agricultural workers committing crimes, based on the data on charges. There is no statistically significant association between temperature or precipitation, and this share.

Table B3. Correlation between the weather and the share of crimes committed by agricultural workers

	Share of crimes committed by agricultural workers
Temperature (°C)	0.0002
	(0.0002)
Precipitations (mm)	0.00007
	(0.00005)

Notes: The dependent variable measured is the share of crimes in day *d* and municipality *i* for which the offender charged of the crime works in agriculture. The model includes average daily temperature and total daily precipitations as explanatory variables. The regression also includes municipality by calendar day (1-365) fixed effects, municipality by month by year fixed effects and a date fixed effect (day-month-year). To ensure that results are representative of total charges, they are weighted by the total number of charges in each municipality, month and year (e.g. Tijuana, May 2006). Standard errors are in parenthesis and clustered at the municipality level.

B.6. Use of Air conditioning and the correlation between temperature and crime

Davis and Gertler (2015) find that the prevalence of air conditioning adoption in Mexico varies across the country. We consider the heterogeneity in the response of criminal charges to temperature in Mexico according to the diffusion of air-conditioning at state level.

Information about the use of air-conditioning (AC) at the state level is available from either the National Surveys of Household Income and Expenditure (ENIGH) (1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012) or the 2018 National Survey on the Consumption of Energy Sources in Private Housing Units (ENCEVI). The Household Income and Expenditure Surveys provide information on the availability of AC in housing units. However, the question was asked differently in 1996-2000, 2002-2006 and 2008-2012. We therefore average out state-level AC diffusion across all surveys to look at differences across the 32 Mexican States (and we avoid using the temporal variation in the data). We also use the 2018 survey on the consumption of energy sources as a robustness check. This survey records if respondents declared using AC. It probably provides the most reliable information on air-conditioning use in Mexico, but the information is for after our study period.

In both sets of surveys, we find large regional differences in AC adoption. For instance, 68 percent of respondents have AC in Sonora in the ENIGH surveys, whereas nearly no respondent has AC in Zacatecas. This is naturally due to differences in geography, since Sonora is very warm whereas Zacatecas is mountainous and, therefore, much cooler.

We interact the share of households with AC (according to either type of surveys) with our weather variables in the baseline model to see if we observe differences in the correlation between the weather and the charge rate according to AC penetration. Results are not statistically significant for temperature and point to a negative association between AC penetration and the impact of rainfall. However, these results should not be interpreted as the impact of AC on the correlation between the weather and crime, since we cannot disentangle the effect of AC from the effect of other differences across states.

Table B4. Interaction between the weather and AC diffusion in Mexican States

Data on AC diffusion	ENIGH 1996-2012	ENCEVI 2018
Column	(1)	(2)
Average daily temperature (in °C)	0.092***	0.098***
	(0.013)	(0.008)
x Share with air conditioning	0.008	0.016
	(0.045)	(0.026)
Total daily precipitations (in mm):	-0.009***	-0.007***
	(0.002)	(0.001)
x Share with air conditioning	-0.018	-0.017***
	(0.012)	(0.006)

Notes: Each column corresponds to a separate regression. The dependent variable is the daily charge rate (all crimes) in crimes per million inhabitants. The model of column (1) is similar to our baseline model, but we have added interactions between the weather and the average share of households with air-conditioning in Mexican State *s* according to the 1996-2012 National Surveys of Household Income and Expenditure (ENIGH). In column 2, we interact the weather variables with the share of respondents in Mexican State s that declared using AC in their homes in the 2018 National Survey on the Consumption of Energy Sources in Private Housing Units. Survey variables on AC adoption and use are constructed using the survey weights (since respondents have a different probability of being in the sample). Regressions include municipality by calendar day (1–365) fixed effects, municipality by month by year fixed effects, and a date fixed effect (day-month-year). Observations are weighted by the population in each municipality. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

C: Robustness checks on short-terms dynamics

In **Appendix C.1**, we provide a few robustness checks on short-term dynamics, including results with a different number of lags and results by type of crime. In **Appendix C.2**, we consider the association between the charge rate of day *d* and the temperatures of the days following the crime.

The displacement effects in **Table 1** are stronger in magnitude to those in Jacob, Lefgren, and Moretti (2007). They found that 65 percent of crimes were additional using U.S. data. We check whether this could be due to a different choice of specification. We use the same specification as Jacob, Lefgren and Moretti (2007) in **Appendix C.3**. We find that about 60 percent of crimes would be displaced crimes with our data. Results in **Appendix C.3** however rely on an IV strategy and an over-identification restriction which are unlikely to hold with our data. This is why we prefer the specification and results of **Table 1**.[1]

C.1. Distributed lag model with 7, 14 and 21 lags, and by type of crimes

Table C1 provides results for distributed lag models, with 7, 14 and 21 lags, and then results by type of crimes with a model with 14 lags. Models only include two variables of interest (average daily temperature and total daily precipitations). We report the results for the coefficient that correspond to the contemporaneous effect of the weather of day *d* on the charge rate of day *d*. We then report the results for the cumulative effect of all lags and the contemporaneous effect together, to assess impacts after 7, 14 and 21 days.

For temperature, we observe displacement effects offsetting nearly 70 percent of the contemporaneous effect after 14 days. In contrast, the effect of precipitations on reducing the charge rate is stronger when we account for precipitations of the day before. This could be because precipitations the day before might be used as an indication to go out and perform some activities (or not) on the next day. The effects by type of crime in **Table C1** suggest that the same effects of displacement for temperature are at play for many types of crimes.

[1] We also looked at the effect of multiple sequential hot days in alternative specifications. We added a variable equal to 1 if the average daily temperatures on day d, d-1 and d-2 were all above 28°C. This variable was not statistically significant in specifications with or without distributed lags. We do not report these results for the sake of concision.

Table C1. Effect of lags on the correlation between the weather and the charge rate

Type of crime and number of lags	Temperature Effect of 1°C Contemporaneous	Temperature Effect of 1°C Cumulative	Precipitations Effect of 1mm Contemporaneous	Precipitations Effect of 1mm Cumulative
All crimes:				
7 lags	0.108***	0.065***	-0.0083***	-0.0159***
	(0.0073)	(0.0174)	(0.001)	(0.0029)
14 lags	0.108***	0.0329**	-0.0083***	-0.0164***
	(0.0074)	(0.0161)	(0.0011)	(0.0041)
21 lags	0.107***	0.037	-0.0083***	-0.0132**
	(0.0074)	(0.0238)	(0.0011)	(0.0051)
Models with 14 lags:				
Homicide	0.0062***	0.0019	-0.0003**	-0.0008
	(0.001)	(0.0019)	(0.0001)	(0.0006)
Injury	0.0272***	0.0094**	-0.0022***	-0.0051***
	(0.0027)	(0.0041)	(0.0003)	(0.0011)
Sexual crime	0.0057***	0.0028	-0.0006***	-0.0014**
	(0.001)	(0.002)	(0.0002)	(0.0006)
Family violence	0.0035***	0.0028**	-0.0003***	-0.0006**
	(0.0006)	(0.0012)	(0.0001)	(0.0003)
Theft	0.0203***	0.0046	-0.0013***	-0.0016
	(0.0027)	(0.0052)	(0.0005)	(0.0018)
Fraud	0.0013**	-0.0013	0.0002	0.0004
	(0.0007)	(0.0014)	(0.0001)	(0.0004)
Property damage	0.0105***	0.002	-0.0001	-0.0012
	(0.0018)	(0.0028)	(0.0002)	(0.0008)
Kidnapping	0.0012*	0.0011	-0.00001	0.0011*
	(0.0007)	(0.0013)	(0.0001)	(0.0005)
Weapon-related crime	0.0083***	0.0017	-0.0013***	-0.0023*
	(0.0024)	(0.0053)	(0.0002)	(0.0013)
Drug-related crime	0.0012	-0.0016	-0.0007***	-0.0009
	(0.0018)	(0.0038)	(0.0002)	(0.0009)
Concerted crime	0.0009	0.0001	-0.0002	-0.0001
	(0.0011)	(0.0027)	(0.0002)	(0.0009)
All other crimes	0.0216***	0.0094	-0.0017***	-0.004**
	(0.0028)	(0.0059)	(0.0004)	(0.0019)

Notes: Each row reports t a separate regression. The dependent variable measured is the daily charge rates (for all crimes or by type of crimes) in charges per million inhabitants. The model only includes average daily temperature and total daily precipitations as explanatory variables, and up to 21 lags for each. The columns for the contemporaneous effects corresponds to the effects of temperature and precipitations on the day, when controlling for the effect of lags. The columns for the cumulative effect of all lags is the sum of all lags and the contemporaneous value. The regressions also include municipality by calendar day (1-365) fixed effects, municipality by month by year fixed effects and a date fixed effect (day-month-year). Observations are weighted by the population in each municipality. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1 .

C.2. Impact of the temperatures and precipitations of the following days

Table C2 shows the impact of temperature and precipitation of the following days on the crime rate today. We find no impact of leads, except for the first lead for temperature. This correlation most likely comes from the correlation in night temperatures between the average temperature on day *d* and the average temperature on day *d-1*. It is also possible that this correlation can come from expectations about the next day weather can potentially be impacted by the weather in the evening and at night.

Table C2. Effect of leads on the correlation between temperature and the charge rate

Independent variables	Average daily temperature	Total precipitations
Contemporaneous value	0.0874*** (0.0095)	-0.009*** (0.0011)
1st lead	0.0374*** (0.0084)	-0.0014 (0.001)
2nd lead	-0.0091 (0.0089)	0.001 (0.0011)
3rd lead	-0.0028 (0.0091)	-0.0001 (0.0011)
4th lead	0.007 (0.0095)	-0.0014 (0.0011)
5th lead	-0.0006 (0.0083)	0.0012 (0.0012)
6th lead	0.0088 (0.0101)	-0.0008 (0.0013)
7th lead	0.0037 (0.0086)	0 (0.0014)
8th lead	0.0147* (0.0077)	0.0026 (0.002)
9th lead	-0.0159* (0.0082)	0.0004 (0.0012)
10th lead	0.0089 (0.007)	-0.0007 (0.0012)
Cumulative effect:		
All leads	0.0521*** (0.0132)	0.0007 (0.0034)
2nd to 10th lead	0.0147 (0.0119)	0.0021 (0.0034)

Notes: Both columns report the results from the same regression. The dependent variable measured is the daily charge rate (all crimes) in crimes per million inhabitants. The model only includes average daily temperature and total daily precipitations as explanatory variables, and ten leads for each. The row for the cumulative effect of all leads is the sum of all leads (from the 1st to the 10th). The row for the cumulative effect of the 2nd to the 10th lead exclude the 1st lead from the calculation of an aggregate effect of leads. The regression includes municipality by calendar day (1-365) fixed effects, municipality by month by year fixed effects and a date fixed effect (day-month-year). Observations are weighted by the population in each municipality. Standard errors are in parenthesis, clustered at the level of municipalities. ***p<0.01, ** p<0.05 and *p<0.1.

C.3. Results with the same model specification as in Jacob, Lefgren and Moretti (2007)

Jacob, Lefgren and Moretti (2007) study the impact of the crime rate at *t-1* on the crime rate at time *t* in a dynamic fixed effect model. Crime rates are computed by dividing the average number of crimes within a week by the total number of crimes in a jurisdiction. They instrument the lagged crime rate with the lagged temperatures. All models include jurisdiction-year fixed effects, month fixed effects, and jurisdiction-specific fourth order polynomials in the day-of-year (in that case, this is the same as the week of year) to control for seasonality.

We follow this approach. We aggregate the data at weekly level and our jurisdictions are the Mexican municipalities. Results are provided in **Table C3**.

Table C3. IV results with same specification as in Jacob, Lefgren and Moretti (2007)

	IV regression
Charge rate the week before	-0.581 (0.089)
Average daily temperature (in °C)	0.014 (0.001)
Average daily precipitations (in mm)	-0.002 (0.0004)
Weak identification test (Kleibergen-Paap rk Wald F statistic)	86.8
Hansen J statistic (p-value)	13.0 (<.001)

Notes: The dependent variable is the weekly charge rate (all crimes) in each municipality, normalized by the average number of charges in each municipality. The model of column only includes the week's average daily temperature and total daily precipitations as explanatory variables, as well as the lagged dependent variable. The specification includes municipality by year fixed effects, month fixed effects, and municipality-specific fourth order polynomials in the the week of year to control for seasonality. Observations are weighted by the average number of charges in each municipality. Standard errors are in parenthesis and clustered at the State by month and year level. The instruments are the first lag of the week's average daily temperature and total daily precipitations.

While the results in **Table C3** align with those of Jacob, Lefgren and Moretti (2007), this model is likely to be inconsistent with our data. Their model relies on a series of assumption, especially the fact that the lagged temperatures at week minus 1 have no impact on the current weekly crime rate except for their impact on the lagged crime rate at week minus 1. With our data, we fail the over-identification test when using temperatures and precipitations at week minus 1 to instrument for the crime rate at week minus 1. This might be because the correct functional form for the impact of lagged crime and temperatures on crime is incorrect with our data (and different from the one in the US). Another possibility is that our lagged temperatures convey some information about the current weather, a point discussed in Jacob, Lefgren and Moretti (2007), that could lead to a violation of the exclusion restriction.

D: Additional tests for sample selection

In **Appendix D.1**, we use different fixed effect structures compared to our baseline specification. Controlling for seasonality at the level of the 32 Mexican States is sufficient to find stable results that are not statistically different from our baseline specification. This suggests that local differences in reporting at municipal level or national day-to-day difference in police effectiveness do not correlate strongly with the weather in a way that would invalidate our results.

In **Appendix D.2**, we then compare the data on charges with those on prosecutions and convictions. We find no statistically significant relationships between the prosecutions-to-charges ratio, the convictions-to-charges ratio and temperature. This suggest that the chances of being prosecuted and convicted once charged are not influenced by the temperature on the day of the crime. However, we find that the proportions of charges that lead to a prosecution and a conviction is lower on rainy days. In **Appendix D.3**, we also exploit the fact that the charges data contains information on whether the crimes recorded were intentional or unintentional (as classified by the police: e.g., car accidents and manslaughter). If warm temperatures encourage opportunistic behavior from offenders, we would expect the proportion of unintentional crimes to be lower during hot days. Yet, the results in **Appendix D.3** show that the proportion of unintentional crimes is stable across cold and hot days, at around 10 percent of crimes. This suggests that criminals do not actively exploit hot days to commit more crimes. Our crime dataset furthermore includes a small proportion (3.18 percent) of crimes classified as failed attempts. Finally, in **Appendix D.4**, we check if failure to accomplish a crime correlates with temperature. We show that, conditional on a crime being undertaken, failed attempts are about 1percent more frequent, in relative terms compared to the sample average, for each additional Celsius degree recorded on the day of the crime. This result is at odds with the idea that criminals would take advantage of hot days because they offer better opportunities. Results in **Appendix D.4** suggests that criminals might be failing more often on hot days.

D.1. Withdrawing fixed effects

Table D1 provides results with different fixed effect structures. For concision, rather than using different temperature and precipitation bins, we use the average temperature and total precipitation as independent variables instead. The baseline specification with linearized effects for temperature is in column 1. OLS results (with no fixed effects, column 2) are not statistically different from the results obtained with our three-way fixed effect model. When controlling for municipality fixed effects and time fixed effects (in column 3), we observe a positive correlation between temperature and crime, but results are attenuated, suggesting that controlling for seasonality matters. The remaining columns (4–7) show that controlling for seasonality at the level of the 32 Mexican States is sufficient to find stable results that are not statistically different from our baseline specification. This suggests that local differences in reporting at municipal level or national day-to-day difference in police effectiveness do not correlate strongly with the weather in a way that would invalidate our results. These results substantially reduce the risk that sample selection drives our results in the baseline model in shown in column 1 of **Table D1** and in **Figure 1**.

Table D1. Correlation between weather and the charge rate with different fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average daily temperature (°C)	0.1022***	0.1500***	0.0588***	0.0921***	0.0919***	0.0815***	0.0866***
	(0.0063)	(0.0262)	(0.0063)	(0.0231)	(0.0259)	(0.0065)	(0.0074)
Total daily precipitations (mm)	-0.0093***	-0.0467***	-0.0114***	-0.0144***	-0.0141***	-0.0110***	-0.0109***
	(0.0010)	(0.0076)	(0.0010)	(0.0023)	(0.0025)	(0.0010)	(0.0010)
Fixed effects:							
Date (day, month, year)	X		X		X	X	X
Municipality			X			X	
State by month				X	X	X	
Municipality by month							X
Municipality by month by year	X						
Municipality by calendar day	X						

Notes: Each column corresponds to a separate regression. The dependent variable is the daily charge rate (all crimes) in crimes per million inhabitants. The models include the average daily temperature and total daily precipitations as explanatory variables. Observations are weighted by the population in each municipality. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05, and *p<0.1.

D.2. Comparing charges to prosecutions and convictions

We run two econometric specifications in the same general form as Eq. (1). However, we change the dependent variable to (i) the prosecution-to-charges ratio and (ii) the convictions-to-charges ratio. These models are furthermore weighted by the average number of charges registered in the municipality of interest, in month *m* and year *t*, thereby results are representative of the number of charges. The prosecution-to-charges ratio is the proportion of criminals that go to trial (prosecutions) over the number of charges. The convictions-to-charges ratio refers to the share of criminals that are found guilty during their trial (convictions) as a proportion of charges.

The main idea behind these models is that if the evidence gathered on a criminal is a function of temperature, then temperature should have an influence on the proportion of charges that lead to a prosecution and then a conviction. This is therefore a partial test for sample selection. If the ability of judges to convict charged individuals depended on the temperature on the day of the crime, then it would be likely that the ability of police to charge them with a crime in the first place would also depend on temperature.

Table D2 show the results when the dependent variable is the prosecution-to-charges ratio in column (1) or the conviction-to-charges ratio in column (2).

Table D2. Impact of the weather on the shares of prosecutions and convictions

	Share Prosecuted (1)	Share Convicted (2)
Temperature (°C)	0.0011	0.0008
	(0.0012)	(0.0012)
Precipitations (mm)	-0.0006***	-0.0004**
	(0.0002)	(0.0002)
Sample average	0.8215	0.7315

Notes: Each column represents a separate regression. The dependent variable is different in each column and corresponds to the share of crimes in municipality *i* and day *d* for which the offender was finally prosecuted (column 1) or convicted (column 2). Results are expressed in absolute terms as the correlation between a change by one Celsius degree or one mm on each share. We provide estimation sample averages in the last row for comparison purposes. Regressions are weighted by the average number of charges recorded in municipality *i*, month *m* and year *t*, to ensure that results are representative of the number of charges recorded in each municipality. Regressions include municipality by calendar day fixed effects, municipality by month by year fixed effects and exact date fixed effects (day, month and year). Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

The results from **Table D2** show that there is no statistical difference between any of the two ratios considered with temperature. This suggests that the chances of prosecution and conviction are not influenced by temperature. **Table D2** also shows that both ratios are negatively related with rainfall. This indicates that crimes committed on rainy days are less likely to be prosecuted or convicted. While this set of results do not rule out sample selection, they provide some evidence that temperatures do not appear to affect the proportion of charges that lead to prosecutions and convictions.

D.3. Unintentional crimes and failed attempts

Our crime dataset also records whether crimes were intentional or unintentional (as classified by the police; e.g. car accidents, manslaughter). In **Table D3**, column 1, we find that the proportion of unintentional crimes is not influenced by temperature. Our crime dataset also includes a small proportion (3.18 percent) of crimes classified as failed attempts. We check if failure to accomplish a crime correlates with temperature (see the last column of **Table D3**). We find that, conditional on a crime being undertaken, failed attempts are about one percent more frequent, in relative terms compared to the sample average, for each additional Celsius degree on the day of the crime.

Table D3. Impact of temperature and precipitations on the shares of accidental crimes and failed attempts

	Share of unintentional crimes (1)	Share of failed attempt (2)
Temperature	-0.0001	0.0003^{***}
(in °C)	(0.0002)	(0.0001)
Precipitations	0.0002^{***}	0.00003
(in mm)	(0.0001)	(0.00003)
Sample average	0.0927	0.0318

Notes: The dependent variable is different in each column. It corresponds to the share of crimes in municipality *i* and day *d* that have been committed unintentionally (column 1) or failed and are classified as attempted crime (column 2), e.g. attempted murder. Results are expressed absolute terms as the correlation between a change by one Celsius degree or one mm on each share. To allow comparisons, we provide estimation sample averages in the last row. Regressions are weighted by the average number of charges recorded in municipality *i*, month *m* and year *t*, to ensure that results are representative of the number of charges recorded in each municipality. Regressions include municipality by calendar day fixed effects, municipality by month by year fixed effects and exact date fixed effects (for each day, month and year). Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1 .

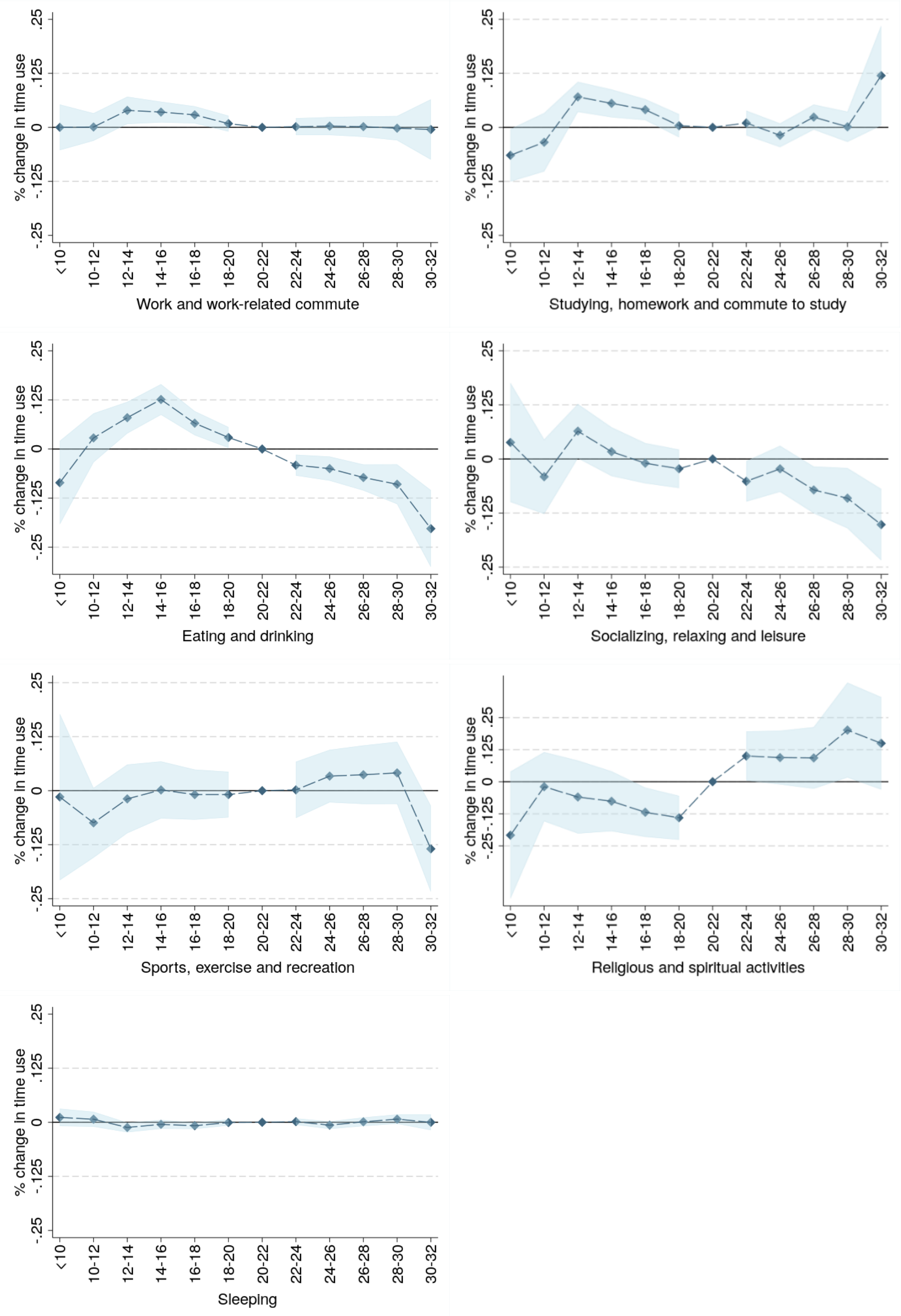
E: Complementary analyses for the impact of the weather on time use

We consider non-linearities in the relationship between time use and temperature in **Appendix E.1**. We find evidence of possible non-linearities, especially at the extremes. For instance, time spent working out may reduce during heat waves (with average temperatures above 30°C). Moreover, the Mexican time use data comes from declarations about a total number of minutes spent on a long list of activities the week before. Thus, the dependent variable is likely to be subject to measurement error since people may not remember very well what they did exactly a week ago. In **Appendix E.2**, we use the American Time Use -Survey (ATUS) (U.S. Bureau of Labor Statistics, 2003-2019). U.S. respondents are asked to record activities for only one day and consequently measurement errors are less of a concern. We observe similar correlations between temperature and activities for most activities in both the U.S. and the Mexican data. Six of the seven categories of activities analysed have the same sign for temperature in the Mexican data as for the Hispanic population of the U.S.

E.1. Mexican time use results with temperature bins

We consider non-linearities in the correlation between time use in the Mexican survey data and temperature. We use a model very similar to Eq. (3), except that, instead of using the average temperature of the week before the interview, we use temperature bins that take a value of 1 if the average temperature of the week before the interview fell within a specific temperature range. Results for all activities are reported in **Figure E1** and they are expressed as a share of the average time spent on each activity in the sample.

Figure E1. Correlation between temperature bins and time use in Mexico



Notes: Results for temperature in panel correspond to different regressions. The dependent variable is the time spent (in minutes, per day on average during the week preceding the interview and as declared by respondents) in the categories mentioned below the x-axis. Regressions include the reported temperature bins, a control for weekly precipitations, interview day fixed effects, municipality fixed effects and a fixed effect for each demographic group (defined based on the respondents' age and gender). We use the survey weights. We drop outliers and respondents no time spent recorded on the activity of the dependent variable, as explained in the main text. The shaded areas correspond to the 95-percent confidence interval. The weather data used is the CPC gridded weather data.

E.2. U.S. Time use survey results

The Mexican time use data comes from declarations about a total number of minutes spent on a long list of activities the week before the interview and consequently the dependent variable is likely to suffer from measurement error. This is considering that people may not remember very well what they did exactly a week ago. Estimates could also be biased if declarations on time use were affected by temperature. This could be the case if temperature had an impact on the number of activities performed, and therefore on the likeliness to forget activities. Furthermore, the data is only available on interview dates for 167 days between 2009 and 2019.

Considering these data limitations, we corroborate the correlations found in the Mexican Surveys on Time Use with U.S. data on time use for comparable activities. Naturally, results with U.S. data cannot be fully transposed to the Mexican context. However, there is some cultural proximity between the Hispanic population in the US and the Mexican people since 62 percent of the Hispanic population of the U.S. is Mexican or of Mexican descent (Pew Research Center, 2019). We focus on the correlation between the weather and time use for the Hispanic population of the US, but we also provide the results for the whole US population for context. For this robustness check, we use the American Time Use Survey (ATUS) (U.S. Bureau of Labor Statistics, 2003-2019). ATUS data files include information from more than 200,000 interviews conducted since 2003. Respondents are asked to record activities for only one day. Therefore, ATUS provides daily data and measurement errors are less of a concern since people may remember more accurately how much time they spent on each activity. We run the following model:

$$(4) \qquad TU_{z,c,d,m,t} = aNT_{c,d,m,t} + u_c + g_{US,d} + \lambda_{n(z_{US})} + \omega_{US,z,c,d,m,t}$$

$TU_{z,c,d,m,t}$ is the time spent by respondent *z*, in minutes on the day of reference, in a given activity in U.S. county c. The subscrits *d*, *m* and *t* correspond to the day, month and year of the reference day. $NT_{i,c,m,t}$ is the vector of climate variables that includes the average temperature and precipitations recorded on the day of reference in county c. u_c is a county fixed effect and $g_{US,d}$ is a day-of-the-year fixed effect (day, month and year). We also create groups of respondents, denoted $n(z_{US})$, based on their age and gender. We then include group fixed effects, denoted $\lambda_{n(z_{US})}$, to control for the impact of age and gender on time use. $\omega_{US,z,c,d,m,t}$ is the error term.

We provide results for categories of activities that match those reported with the Mexican surveys. Naturally, the match between the activities recorded in the Mexican and U.S. surveys is imperfect, since questions are asked differently, but the activities for which we provide information are generally comparable across both surveys.

Results with ATUS data are provided in columns 2 and 3 of **Table E1**, for the Hispanic population and the U.S. population as a whole. In column 1 of **Table E1**, we report the results of **Table 5**, as obtained previously with the Mexican surveys on Time Use.

We observe similar correlations between temperature and activities for most activities in both the U.S. and the Mexican data. Six of the seven listed activities have the same sign for temperature in the Mexican data as for the Hispanic population of the U.S.[2] Results are much less precise for precipitations with the Mexican data, and therefore less convergent between both datasets. Results between the overall U.S. population and the Hispanic population of the US are similar. Differences between columns could stem from statistical imprecision, as well as differences in the studied populations or exposure to a different range of temperatures: Mexico is warmer, and the Hispanic population is not evenly spread across the U.S.

[2] The coefficient for sleeping time and temperature is however statistically negative for the U.S. Hispanic population, whereas it is positive but not statistically significant with the Mexican data.

Table E1. Correlation between the weather and time use in Mexico and the United States

Column number	(1)	(2)	(3)
Origin of Time Use Survey	Mexico	U.S.	
Sample	Mexico	US Hispanic	All US
Effect of temperature (in C):			
Work and work-related commute	-1.13***	-0.09	0.19
	(0.41)	(0.58)	(0.27)
Studying, homework and commute to study	-1.07***	-0.46*	-0.25**
	(0.38)	(0.26)	(0.12)
Socializing, relaxing and leisure	-1.07***	-0.60	-0.5**
	(0.33)	(0.39)	(0.19)
Sports, exercise and recreation	0.14	0.38***	0.22***
	(0.09)	(0.12)	(0.05)
Religious and spiritual activities	0.42***	0.25***	0.03
	(0.1)	(0.09)	(0.04)
Sleeping	0.22	-0.55**	-0.1
	(0.18)	(0.28)	(0.12)
Eating and drinking	-0.90***	-0.18*	-0.002
	(0.12)	(0.11)	(0.05)
Effect of precipitations (in mm):			
Work & Work-Related Commute	-0.21	0.50	0.11
	(0.31)	(0.33)	(0.18)
Studying, homework and commute to study	0.15	-0.34*	-0.05
	(0.28)	(0.19)	(0.07)
Socializing, relaxing and leisure	-0.59**	-0.16	0.09
	(0.24)	(0.21)	(0.13)
Sports, exercise and recreation	-0.05	0.02	-0.04
	(0.08)	(0.06)	(0.03)
Religious and spiritual activities	0.11	-0.001	-0.03
	(0.08)	(0.05)	(0.02)
Sleeping	0.21	0.13	0.12
	(0.14)	(0.23)	(0.09)
Eating and drinking	-0.09	0.14*	0.05
	(0.06)	(0.08)	(0.03)

Notes: Results for temperature in each row and column correspond to different regressions. The results for precipitations are taken from the same regression as the results for temperature corresponding to the same activity and population sample. With the Mexican data on time use, the dependent variable is the time spent (in minutes, per day on average during the week preceding the interview and as declared by respondents) in the categories mentioned in the rows. Regressions include interview day fixed effects, municipality fixed effects and a fixed effect for each demographic group (defined based on the respondents' age and gender). We use the survey weights and drop outliers and respondents no time spent recorded on the activity of the dependent variable, as explained in the main text. Temperature and precipitations correspond to the average daily value during the week of reference. With the U.S. data, the dependent variable is the time spent in minutes during the day of reference and the dependent variable are the average daily temperature and rainfall. We did not drop outliers and kept the whole sample, since this data is less subject to measurement error. Standard errors are shown in parenthesis and clustered at the municipality / county level. The weather data used in both analyses is the CPC gridded weather data, which covers both the U.S. and Mexico. ***p<0.01, ** p<0.05 and *p<0.1.

F: Additional evidence on time use and victimization risks

In **Appendix F.1**, we show that U.S. respondents spend less time at home on warm days, including during the night. We also find that they spend more time in activities that may expose them to crime at night: they happen to be walking or outdoors away from home at night more often on warmer days. We do not have similar information for Mexico. However, in **Appendix F.2**, we use night-time light data from NASA (Roman et al. 2018) and show that night-time light in Mexico is responsive to changes in the weather. While we cannot describe which activities are associated with more night-time light (some of them could be industrial activities), this result suggests that changes in night-time activities correlate with temperature in Mexico. In **Appendix F.3.**, we use data from the criminal investigation files (*Fiscalía General de Justicia 2021*) of Mexico City that provides information on the hour when crimes are committed. Conditional of a crime having happened, we estimate the probability that it occurred at a specific moment of the day as a function of temperature. At higher temperatures, we observe an increase in the share of crimes committed in the late afternoon and at night (from 6pm to 6am). Finally in **Appendix F.4.**, we study the correlation between the average monthly temperature and the number of acts of vandalism per million inhabitants using the victimization survey data.

F.1. Respondents' location in ATUS by time of day

For each activity recorded in ATUS, respondents provide information on location, starting time and duration. We can therefore extrapolate how much time respondents spent in each recorded location at different times of day. We aggregate this information by 6-hour periods and for any time of the day. We then run regressions following Eq. (4). The dependent variable is the time spent by respondents, during the day of reference, in a declared location for a given time of day.

Table F1 shows the results for three categories: at home (includes in the yard); outside away from home; and anywhere else (includes in any type of transport or any indoor space apart from home). Temperature positively correlates with time spent away from home. Results by time of day suggest that people spend more time outdoors away from home between 6pm and 12am on warmer days.

Table F1. Correlation between the weather any location in the United States, by time of day

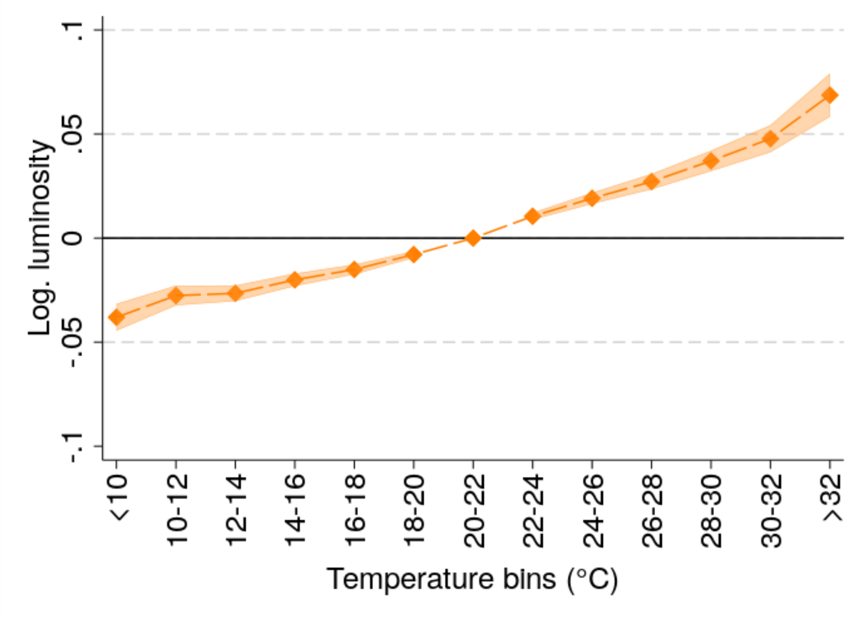
Activities	Any time of day	Morning (6am to 12pm)	Afternoon (12pm to 6pm)	Evening (6pm to 12am)	Early morning (0am to 6am)
Effect of temperature (in C):					
Time at home	-0.491*	-0.209**	-0.132	-0.135	-0.015
	(0.28)	(0.106)	(0.142)	(0.131)	(0.046)
Time outside away from home	0.125**	0.001	0.041	0.078***	0.005
	(0.053)	(0.021)	(0.028)	(0.019)	(0.007)
Time anywhere else	0.531*	0.247*	0.16	0.07	0.051
	(0.297)	(0.129)	(0.148)	(0.128)	(0.043)
Effect of precipitations (in mm):					
Time at home	0.12	0.042	0.126	-0.016	-0.032
	(0.183)	(0.063)	(0.088)	(0.077)	(0.025)
Time outside away from home	-0.086***	-0.021*	-0.053***	-0.003	-0.009**
	(0.029)	(0.013)	(0.015)	(0.011)	(0.004)
Time anywhere else	-0.109	-0.014	-0.105	0.022	-0.013
	(0.208)	(0.086)	(0.094)	(0.073)	(0.03)

Notes: Results for temperature in each row and column correspond to different regressions. The results for precipitations are taken from the same regression as the results for temperature corresponding to the same activity and population sample. Regressions include interview day fixed effects, municipality fixed effects and a fixed effect for each demographic group (defined based on the respondents' age and gender). We use the survey weights of the surveys. Temperature and precipitations correspond to the average daily value during the week of reference. The dependent variable is the time spent in minutes during the day of reference and the dependent variable are the average daily temperature and rainfall. Standard errors are shown in parenthesis and clustered at the municipality / county level. The weather data is the CPC gridded weather data.

F.2. Correlation between the weather and night-time light

A limitation of using Mexico's time use surveys is that the data is limited to only 107 interview days. It also comes from declarations that are prone to measurement error. Thus, we complement our time use survey results with satellite night-time light data covering Mexico since January 2012 from NASA (Roman et al., 2018). Using the satellite data of Roman et al. (2018) allows us to rely on data of wider coverage, and higher accuracy since this is observed and not reported data. **Figure F1** below provides the result of an econometric model where we explain a change in the log of the average night-time luminosity recorded in each municipality and each day in Mexico, with a specification similar to Eq. (1). We find a positive association between temperature and night-time light intensity. This suggests that weather influences time use.

Figure F1. Correlation between night-time light intensity and daily temperature



Notes: The dependent variable measured in the y-axis is the average log. intensity of night-time lights in municipality *i* on day *d*, month *m* and year *t*. It is measured in nWatts per square centimetre steradian and has been corrected for lunar irradiance and missing data due to cloud cover. The regression also includes municipality by calendar day (1-365) fixed effects, municipality by month by year fixed effects and a date fixed effect (day-month-year). The regression also controls for total precipitations in mm and for the share of missing data in each municipality (caused by cloud cover) to ensure that results are not driven by other climatic factors. Observations are weighted by the population in each municipality. The solid line corresponds to the point estimates, while the 95% confidence intervals are indicated by the shaded areas for standard errors clustered at the municipality level. The reference bin is 20-22°C.

F.3. Hour of crime in Mexico City

The criminal investigation files (*Fiscalía General de Justicia 2021*) of Mexico City provide information on the hour when crimes are committed. Conditional of a crime having happened, we estimate the probability that it occurred at a specific moment of the day as a function of temperature. We use linear probability models (due to the high number of fixed effects) and include municipality by calendar day fixed effects and municipality by month and year fixed effects. Results are provided in **Table F2**.

At higher temperatures, we observe an increase in the share of crimes committed in the late afternoon and at night (from 6pm to 6am). This change in the timing of crimes suggest that exposure to crime might increases especially at night. Interestingly, the coolest hours of the day (i.e. the evenings and nights) seem to be those that drive criminality at higher temperatures. This may be because households may prefer to perform some activities later in the day to avoid exposure to the warmest temperatures of the day, or because temperatures at night are more comfortable on warm days and therefore people could be more likely to go out.

Table F2. Weather and conditional probability of crime by time of day in Mexico City

	Probability of a crime happening in the:			
	Morning (6am to 12pm)	Afternoon (12pm to 6pm)	Evening (6pm to 12am)	Early morning (0am to 6am)
Average daily temperature (°C)	-0.0005	-0.0013**	0.0013**	0.0014***
	(0.0005)	(0.0006)	(0.0006)	(0.0004)
Total daily precipitations (mm)	0.001***	0.001***	-0.0006**	-0.0017***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)

Notes: Each column corresponds to separate linear regressions. The dependent variables are equal to 1 if the crime recorded in the data happened at the specified time (e.g., 6am to 12pm) and zero otherwise. The model includes municipality by calendar day fixed effects and municipality by month and year fixed effects. We do not include date fixed effects because the 16 municipalities of Mexico City are very close to each other and most weather variations would be captured. We only use data for crimes committed in Mexico City from 2017 onwards, since they gather more than 98 percent of crimes in the data (some crimes committed before have been reported at a later data and included in this dataset; some crimes were committed outside of Mexico City). The weather data used comes from the Climate Predictions Center. Standard errors are in parenthesis and clustered at municipality level. ***p<0.01, ** p<0.05, and *p<0.1.

F.4. Weather and vandalism in survey data

Table F3. Correlation between the weather and vandalism rates in survey data

	Vandalism acts at all temperatures	Vandalism acts at average temperature between 18-23°C
Average monthly temperature (°C)	52.0***	97.5*
	(13.1)	(52.8)
Total monthly precipitations (mm)	-9.5	-41.2*
	(7.6)	(21.4)
Impact of 1°C relative to sample average	2.08%***	3.84%*
	(0.52%)	(2.08%)

Notes: Each column corresponds to a separate regression. The dependent variable is the vandalism rate in crimes per million inhabitants per month. The models include the average monthly temperature and total monthly precipitations as explanatory variables. Regressions include municipality fixed effects and period fixed effects (month by year). Observations are weighted by the population in each municipality. The last row for the relative impact of 1°C is equal to the coefficient obtained for the impact of the average monthly temperature, divided by the sample average of the dependent variable. Standard errors are in parenthesis and clustered at municipality level. ***$p<0.01$, ** $p<0.05$, and *$p<0.1$.

G: Additional evidence on the weather and alcohol consumption in Mexico

In Apendix G.1., we use the Mexican Survey on Household Income and Expenditure for 2012, 2014, 2016, 2018 and correlate purchases of alcohol with the weather. We find a statistically significant correlation between alcohol purchases and temperature with a distributed lag models, suggesting that people may consume more alcohol because of warm temperatures. The positive effect comes from temperatures between 1-3 days before the purchase. We find no impact for deeper lags (days 4-6 before the purchasing day) or for temperatures on the day. In **Appendix G.2.**, we analyze internet searches for "alcoholic beverages" and correlate that with the weather. The data is available monthly at the state level. We find a positive statistically significant correlation between alcoholic beverages internet searches and temperature.

G.1. Alcohol purchases

The Mexican Survey on Household Income and Expenditure (INEGI, 2012, 2014, 2016, 2018) provides information on daily alcohol purchases by respondents on the week preceding the interview.[3] We can therefore look at the correlation between alcohol purchases and temperature over seven days for each respondent.

When doing so, we account for two factors. Firstly, many respondents may not buy alcohol over a week because this is a very short period. Therefore, our preferred specification includes municipality fixed effects, and not household fixed effects because the latter would discard valuable information about non-alcohol-purchasing households. Analyzing correlations at a broader level allows us to account for this problem. Secondly, alcohol is non-perishable and may be bought on a different day. We use a distributed lag model (similar to Eq. 2) to account for the impact of temperature a few days before. We could find delayed impacts if household consumed their stocks of alcohol at higher temperatures and replenished them on the following days, a scenario that is very likely since households usually store alcohol.

The dependent variable consists of daily purchases of alcohol expressed in millilitres of pure

[3] This information is not available with the same precision for the waves before 2012. We cannot identify the precise day of purchase in earlier waves and therefore only use data from 2012 onwards. We excluded the 2020 wave from the analysis due to the Coronavirus pandemic possibly affecting the results for that year.

alcohol, for respondent z in municipality i, on day d of month m and year t.[4] Considering that there is under-reporting in the dataset, and that total alcohol purchases may be measured with error (since we do not know the exact alcohol content of every drink, for instance), we also provide regressions where the dependent variable is a dummy variable equal to one each time alcohol was purchased by respondent z in municipality i, on day d of month m and year t. The independent variables are the average daily temperature and average precipitations. We provide results with 3 lags and 6 lags, giving up to a week for consumers to replenish alcohol stocks. We also provide results with no lag at all. We include municipality and date fixed effects to ensure that changes in temperature do not correlate with unobserved factors and weigh the regressions with the corresponding survey weights.

Results are provided in **Table G1**, we observe a statistically significant correlation between alcohol purchases and temperature with the distributed lag models, suggesting that people may consume more alcohol because of warm temperatures. The positive effect appears to come mostly from warm temperatures between 1-3 days before the purchase. We find no impact for deeper lags (days 4-6 before the purchasing day).

Using the same data, we found that general purchases (all goods) correlate negatively with on-the-day temperature.[5] Therefore, people may or may not buy more alcohol on hot days since they buy less of everything on these days in general. However, we find an increase in alcohol purchases due to hot days after accounting for the delayed impact of temperature on alcohol purchases, possibly because people would replenish their stocks after a hot day.

[4] The data records the alcohol purchases, in litres, for several categories of alcohol. Based on online searches for the alcohol content of various products, we made the following assumptions regarding the alcohol content of the categories of alcohol recorded in the data: Cognac and brandy (40 percent), Beer (5 percent), Anise (liqueur) (40 percent), Sherry (17 percent), Liquor or fruit creams (17 percent), Aguamiel, pulque, tlachique (6 percent), Aguardiente, cane alcohol, charanda, mezcal (55 percent), Aged rum, white, with lemon (40 percent), Eggnog (10 percent), White and pink cider (5 percent), Aged, blue and white tequila (40 percent), White, rosé, red table wine (10 percent), Vodka (45 percent), Whiskey (40 percent), Prepared alcoholic beverage (10 percent), Other alcoholic beverages: champagne (12 percent). The vast majority of purchases correspond to beer purchases.

[5] Results for the correlation between total purchases (in Mexican pesos) and the weather are not shown for concision.

Table G1. Correlation between the weather and alcohol purchases in the Mexican Survey of Household Income and Expenditure

	Sales (in mm of pure alcohol)			Alcohol has been purchased (dummy variable)		
Specification	No lags (1)	With 3 lags (2)	With 6 lags (3)	No lags (4)	With 3 lags (5)	With 6 lags (6)
Average daily temperature (in °C):						
Effect on the day	0.017	-0.047	-0.044	0.0004**	0.0002	0.0002
	(0.037)	(0.042)	(0.042)	(0.0002)	(0.0001)	(0.0002)
Cumulative effect (on the day + 3 lags)		0.089**	0.109**		0.0007***	0.0007***
		(0.044)	(0.047)		(0.0002)	(0.0002)
Cumulative effect (on the day + 6 lags)			0.080*			0.0006**
			(0.048)			(0.0003)

Notes: Each column corresponds to a separate regression. The dependent variable is the daily purchase of pure alcohol (in ml) or a dummy variable equal to 1 if alcohol has been purchased, and 0 otherwise. The model of columns (1) and (4) only includes average daily temperature and total daily precipitations as explanatory variables. The models of columns (2)-(3) and (5)-(6) also include, respectively, 3 and 6 lags for the daily average temperature on the previous days. The row for "Cumulative effect (on the day + 3 lags)" display the cumulative effect of adding the coefficient from the temperature on the day and the three lags corresponding to the temperature of the three days before. "Cumulative effect (on the day + 6 lags)" display the cumulative effect of adding the coefficient from the temperature on the day and the six lags corresponding to the temperature of the six days before. For concision, results for precipitations (statistically insignificant) are not reported. Regressions also include municipality fixed effects and a date fixed effect (day-month-year). Observations are weighted with survey weights. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

G.2. Online searches for terms related to “alcoholic beverages”

We downloaded Google trends data on the topic called “alcoholic beverages” (as defined by Google’s algorithms to include keywords such as “beers” or “alcohol sales”) for each of the 32 Mexican States. The variable recorded by Google is a measure of search interest, from 0 to 100, relative to the highest point in each State since 2004. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term, so we exclude all 0 from the analysis. The average interest in the dataset is equal to about 36. The data is available monthly since 2004, however, due to internet searches being less widespread in Mexico in the early 2000s, the variance in the data is about 40 percent higher in 2004-2010 compared to later years.

In **Table G2**, we provide the results of models in which we correlate the data on interest for alcoholic beverages with the CPC weather data. The weather data has been aggregated to be monthly and at State level. The specification includes State fixed effects, month-by-year fixed effects, and is weighted according to the population in each State. We provide results for the full sample (column 1) as well as the reduced, more precise sample after 2010 (column 2).

Table G2. Correlation between the weather and internet searches about alcoholic drinks in Mexico

Sample	2004-2019	2011-2019
Average monthly temperature(°C)	0.093	0.169**
	(0.086)	(0.072)
Total monthly precipitations (mm)	-0.049	-0.124
	(0.099)	(0.104)

Notes: Each column corresponds to a separate regression. The dependent variables is the level of online interest for “alcoholic drinks” as calculated by Google algorithms. The average monthly temperature and total monthly precipitations at State level are the explanatory variables. They are calculated by averaging out municipality values and are weighted according to the population in each municipality. Regressions include State fixed effects and month-by-year fixed effects. Observations are weighted by the population in each State. Standard errors are in parenthesis and clustered at the State level. ***p<0.01, ** p<0.05, and *p<0.1.

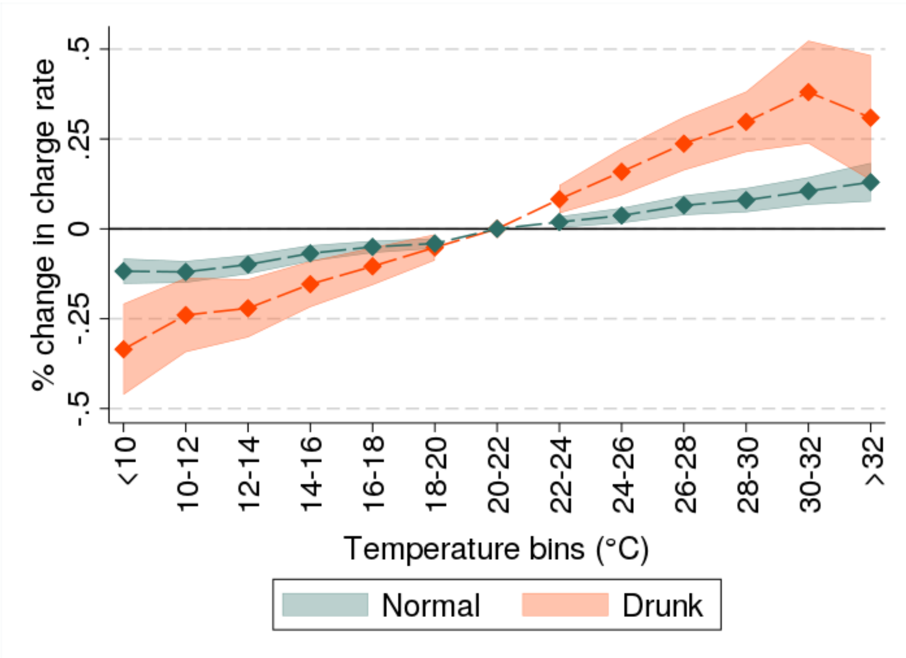
H: Additional results on the interaction between the weather, temperature, and crime

In **Appendix H.1**, we consider non-linearities and use temperature bins to look at the correlation between the weather and crime for drunk offenders and those sober. In **Appendix H.2**, we restrict the sample to days with average temperatures between 18°C and 23°C to estimate the correlation between temperature and the daily charge rate for drunk offenders and those in normal state. In **Appendix H.3**, we also study the correlation between the weather and the probability that an incident reported in the victimization survey data was perpetrated by an individual under the influence of alcohol. While we observe no statistically significant difference between the proportion of offenders under the influence of alcohol during the day, we observe a statistically significant and positive association between temperature and the proportion of criminals under the influence of alcohol at night (midnight to 6am).

H.1. The association between temperature bins and charge rates for offenders in normal state and drunk offenders

Figure H1 shows the estimated correlation between temperature and charges, separately for drunk offenders and offenders in normal state. We follow Eq. (1) and use temperature and precipitation bins. Thus, the specification is similar to that reported in **Figure 1**.

Figure H1. Daily correlation between charges and temperature, for drunk offenders and offenders in normal state



Notes: This graph reports the results of two distinct regressions (offenders in normal state in blue, and drunk offenders in red). The dependent variable is the daily charge rate per million inhabitants, normalized on the y-axis according to the average charge rate of each population of offenders (in normal state or drunk). We report the results of each regression for all the temperature bins (on the x-axis). Regressions include municipality by calendar day (1–365) fixed effects, municipality by month by year fixed effects, and a date fixed effect (day-month-year). It also includes six precipitation bins (no rain, 0–5mm, 5–10mm, 10–15mm, 15–20mm, and above 20mm). Observations are weighted by the population in each municipality. The solid line corresponds to the point estimates, while the 95% confidence intervals are indicated by the shaded areas for standard errors clustered at the municipal level. The reference bin is 20–22°C for temperature.

H.2. Temperature and charge rates for offenders in normal state and drunk offenders at comfortable average temperatures (18-23°C).

Table H1. Correlation between temperature and charge rates for offenders in normal state and drunk offenders at comfortable average temperatures (18-23°C).

Health status of criminal	Normal state			Drunk		
	Charge	Effect of 1°C		Charge	Effect of 1°C	
Crime category	rate	Absolute	Relative	rate	Absolute	Relative
All crimes	4.65	0.0884***	1.9%***	0.77	0.0224***	2.92%***
		(0.0142)	(0.31%)		(0.0051)	(0.67%)
By gender:						
Male offenders	8.66	0.171***	1.97%***	1.58	0.0452***	2.86%***
		(0.026)	(0.3%)		(0.0107)	(0.68%)
Female offenders	1.06	0.0142*	1.34%*	0.03	0.0017	5.73%
		(0.0077)	(0.72%)		(0.0012)	(4%)
By age group:						
Offenders below 25	7.37	0.135***	1.83%***	1.33	0.0311**	2.34%**
		(0.036)	(0.49%)		(0.0142)	(1.07%)
Offenders aged 25-65	7.39	0.138***	1.87%***	1.18	0.0397***	3.36%***
		(0.0241)	(0.33%)		(0.0091)	(0.77%)
Offenders above 65	1.32	0.0436*	3.3%*	0.1	-0.0041	-4.05%
		(0.0233)	(1.77%)		(0.006)	(5.91%)

Notes: This table replicates the regressions and results of **Table 10** while using exclusively observations from days with an average daily temperature between 18 and 23°C. Each row provides results from two separate regressions. The charge rates are for the estimation samples and differ from the average charge rate in the entire dataset. The effect of 1°C corresponds to the coefficient for average temperature in regressions based on Eq. (1). Estimates are expressed in absolute terms, i.e. in charges per million people in each demographic group, and relative to the charge rate in the estimation sample. Regressions include municipality by calendar day fixed effects, municipality by month by year fixed effects, and exact date fixed effects (day, month and year). The regression also controls for precipitations in mm Observations are weighted by the population in each municipality. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

H.3. Incidents under the influence of alcohol in the victimization data

We estimate the correlation between the weather and the probability that an incident reported in the victimization survey data was perpetrated by an individual under the influence of alcohol. The information is provided at different times of day. We observe an increase of incidents under the influence of alcohol at night. There is also weak evidence of a reduction in the evening (6pm to 12am). It could be that some people consume alcohol later on hot days, explaining some displacement in crimes under the influence of alcohol from the evening to the night.

Table H2. Effect of 1°C on the probability of an offense committed under the influence of alcohol in the SVPPS data

	Anytime of day	Morning (6am to 12pm)	Afternoon (12pm to 6pm)	Evening (6pm to 12am)	Early morning (0am to 6am)
All incidents	-0.019	-0.012	-0.02	-0.038*	0.089**
	(0.012)	(0.03)	(0.021)	(0.022)	(0.035)

Notes: Results in each cell are from separate logistic regressions. The dependent variable is one if the incident in the SVPPS data took place at the indicated time (in the column), and zero otherwise. The regressions include: period fixed effects (month by year); municipality fixed effects; crime category fixed effects (13 categories of the survey); fixed effects for the nature of the main damage from the crime (economic or laboral; physical; emotional; or none); control variables for the victim's age and age squared; fixed effects for the victim's gender, educational attainment (9 categories) and family role in the household (6 categories, i.e. spouse); fixed effects for the age range of the offender; if they acted alone; their gender (with a value of 1 for men, and 0.5 if there was an equal amount of men and women); if the offender carried a weapon. They also include monthly total precipitations as an additional control variable. Regressions use survey weights. Standard errors are in parenthesis and clustered at municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

I: Robustness checks to understand better the effect of weekends on crime

In **Appendix I.1**, we check that the effect of weekends does not stem from changes in deterrence. In **Appendix I.2** we provide separate results for weekends and weekdays within comfortable temperatures (18–23°C). For all crimes, we find that an increase in temperature by 1°C leads to an increase in the charge rate by 1.41 percent [0.80–2.02] on weekdays and 2.6 percent on weekends [1.33–3.87]. Results are therefore very similar, even though less precise since they rely on a smaller sample. In **Appendix I.3**, we run two econometric models while reducing the estimation period to all observations between Dec 21st and January 1st (all years); and January 2nd to 13th. This allows us to compare a period of holidays with high levels of social interactions, with a much calmer period following New Year's Eve. Results suggest that the effect of temperature on crime may be nearly twice larger in the holiday period preceding New Year's Eve. Effects are, however, not statistically different due to the smaller sample size.

I.1. Impact of temperature on the outcomes the share of prosecutions, convictions, unintentional crimes and failed attempts for weekdays and weekends

We reproduce the tests for sample selection of **Appendices D.2, D.3 and D.4,** separately for weekends and weekdays. Tests suggest that temperature has no effect on sample selection on weekends and weekdays.

Table I1. Impact of temperature and precipitations on the shares of prosecutions, convictions, accidental crimes and failed attempts, separately for weekdays and for weekends

Panel A: weekdays

	(1)	(2)	(3)	(4)
Dependent Variable	Share prosecuted	Share convicted	Share of unintentional crimes	Share of failed attempts
Temperature	0.0008	0.0006	0.0001	0.0004***
(in °C)	(0.0011)	(0.0010)	(0.0002)	(0.0001)
Precipitations	-0.0005**	-0.0004**	0.0002***	0.00005
(in mm)	(0.0003)	(0.0002)	(0.0001)	(0.00004)

Panel B: weekends

Dependent Variable	Share prosecuted	Share convicted	Share of unintentional crimes	Share of failed attempts
Temperature	0.0054	0.0049	-0.0007	-0.0002
(in °C)	(0.0049)	(0.0046)	(0.0006)	(0.0003)
Precipitations	-0.0002	-0.0001	0.0001	-0.0001
(in mm)	(0.0004)	(0.0005)	(0.0001)	(0.0001)

Notes: Panel A corresponds to weekdays, and Panel B to weekends. The dependent variable is different in each column. It corresponds to the share of crimes in municipality *i* and day *d* for which the offender was finally prosecuted (column 1) or convicted (column 2); and to the share of crimes in municipality *i* and day *d* that have been committed unintentionally (column 3) or failed and are classified as attempted crime (column 4), e.g. attempted murder. Results are expressed absolute terms as the correlation between a change by one Celsius degree or one mm on each share. Regressions are weighted by the average number of charges recorded in municipality *i*, month *m* and year *t*, to ensure that results are representative of the number of charges recorded in each municipality. Regressions include municipality by calendar day fixed effects, municipality by month by year fixed effects and exact date fixed effects (for each day, month and year). Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

I.2. Weekdays vs. weekends within comfortable temperatures (18 to 23°C)

Table I2. Effect of temperature on charge rates on weekdays vs. weekends (18-23°C)

Day of week		Weekday			Weekend	
	Charge	Effect of 1°C		Charge	Effect of 1°C	
Crime category	rate	Absolute	Relative	rate	Absolute	Relative
All crimes	5.71	0.0803***	1.41%***	6.24	0.162***	2.6%***
		(0.0179)	(0.31%)		(0.0408)	(0.65%)
By gender:						
Male offenders	10.70	0.168***	1.57%***	12.00	0.314***	2.62%***
		(0.0352)	(0.33%)		(0.0819)	(0.68%)
Female offenders	1.21	0.0001	0.01%	1.04	0.0198	1.9%
		(0.0089)	(0.74%)		(0.0173)	(1.66%)
By offenders age group:						
<25	8.94	0.135***	1.51%***	11.00	0.254**	2.31%**
		(0.0479)	(0.54%)		(0.11)	(1%)
25-65	9.12	0.119***	1.3%***	9.48	0.257***	2.71%***
		(0.0319)	(0.35%)		(0.0747)	(0.79%)
65+	1.58	0.0256	1.62%	1.37	-0.0443	-3.23%
		(0.0308)	(1.95%)		(0.0587)	(4.28%)
Drunk offenders:						
All crimes	0.62	0.0133**	2.16%**	1.14	0.0236	2.07%
		(0.0052)	(0.85%)		(0.0155)	(1.36%)
Offenders in normal state:						
All crimes	4.66	0.0625***	1.34%***	4.61	0.126***	2.73%***
		(0.016)	(0.34%)		(0.032)	(0.69%)
Homicide	0.14	0.0036	2.55%	0.20	0.0213***	10.92%***
		(0.0023)	(1.66%)		(0.0069)	(3.51%)
Injury	0.60	0.0102**	1.7%**	0.86	0.0381***	4.41%***
		(0.0042)	(0.71%)		(0.011)	(1.27%)
Sexual crime	0.19	0.0051**	2.64%**	0.18	-0.0073	-3.98%
		(0.0024)	(1.28%)		(0.0051)	(2.76%)
Family violence	0.06	0.0014	2.21%	0.06	0.0037	5.88%
		(0.0011)	(1.7%)		(0.0022)	(3.61%)
Theft	1.47	0.0195**	1.33%**	1.35	-0.012	-0.89%
		(0.0088)	(0.6%)		(0.0125)	(0.93%)
Fraud	0.12	0.00168	1.4%	0.07	0.00569*	7.69%*
		(0.0018)	(1.46%)		(0.003)	(4%)
Property damage	0.35	0.0047	1.34%	0.43	0.0265***	6.18%***
		(0.0035)	(0.99%)		(0.0071)	(1.65%)
Kidnapping	0.06	0.0018	3.19%	0.04	-0.0008	-2.13%
		(0.0019)	(3.39%)		(0.0032)	(8.28%)
Weapon-related crime	0.40	0.0028	0.71%	0.41	0.0132	3.21%
		(0.0041)	(1.05%)		(0.0089)	(2.16%)
Drug-related crime	0.42	0.0037	0.88%	0.33	-0.0004	-0.11%
		(0.0047)	(1.12%)		(0.0088)	(2.64%)
Concerted crime	0.07	0.0016	2.17%	0.06	0.0078	12.58%
		(0.0027)	(3.69%)		(0.0054)	(8.7%)
All other crimes	0.78	0.0065	0.83%	0.61	0.03***	4.9%***
		(0.0061)	(0.79%)		(0.0112)	(1.83%)

Notes: Sample is reduced to days with a temperature between 18 and 23°C. Each set of rows provides results from two separate regressions: weekdays and weekends. The charge rates reported in the table are for the estimation sample and differ from the average charge rates in the entire dataset. The effect of 1°C corresponds to the coefficient for average temperature in regressions based on Eq. (1). Estimates are expressed in absolute terms, i.e. in charges per million people in each demographic group, and relative to the charge rate in the estimation sample. Regressions include municipality by calendar day fixed effects, municipality by month by year fixed effects, and exact date fixed effects (day, month and year). The regression also controls for precipitation in mm. Observations are weighted by the population in each municipality. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05 and *p<0.1.

I.3. Effect of temperature on crime before and after New Year's Eve

We reduce the estimation period to all observations between Dec 21st and January 1st (all years); and January 2nd to 13th. This allows us to compare a period of holidays with high levels of social interactions, with a much calmer period following New Year's Eve.

Table I3. Effect of temperature on the charge rate before and after New Year's Eve

		Temperature Effect of 1°C		Precipitations Effect of 1 mm	
Period	Charge rate	Absolute	Relative	Absolute	Relative
Dec. 21 to Jan. 1st	5.07	0.105***	2.07%***	-0.0303**	-0.6%**
		(0.0259)	(0.51%)	(0.0144)	(0.28%)
Jan. 2nd to Jan. 13th	5.19	0.060*	1.16%	-0.0076	-0.15%
		(0.0327)	(0.63%)	(0.0081)	(0.16%)

Notes: Each row corresponds to a separate regression. The dependent variable is the daily charge rate (all crimes) in crimes per million inhabitants. The models include the average daily temperature and total daily precipitations as explanatory variables. The two regressions also include municipality by calendar day (1-365) fixed effects, municipality by month by year fixed effects and a date fixed effect (day-month-year). Observations are weighted by the population in each municipality. Standard errors are in parenthesis and clustered at the municipality level. ***$p<0.01$, ** $p<0.05$ and *$p<0.1$.