Understanding the Link between Temperature and Crime

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Abstract

The correlation between hot weather and crime is well documented but not fully understood. We combine millions of administrative records, victimization surveys on unreported crime and daily weather information to analyze the effect of temperatures on crime in Mexico. We find that sample selection cannot explain the observed positive correlation between temperature and crime. Moreover, we find that shifts in alcohol consumption and time use on weekends are responsible for 28 percent of temperature-induced crimes. We also observe changes in the hour and location of crimes, providing new evidence on the importance of time use as a determinant of crime.

Keywords: temperature; crime; time use; deterrence; alcohol

JEL codes: D91; K42; Q54

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Introduction

Previous studies have consistently shown a positive correlation between high temperatures and crime rates.* However, the exact mechanisms driving this correlation are still not fully understood (Baysan et al. 2019; Blakeslee et al. 2021). A common view is that high temperatures have an impact on human physiology and, thus, influence aggressiveness. However, this physiological channel is still under study (Blakeslee et al. 2019, Mukherjee and Sander 2021, Almås, Ingvild, et al. 2019) and the available evidence does not discard competing explanations, such as changes in time use or deterrence on hot days. Furthermore, crimes are usually under-reported for reasons that could possibly correlate with temperatures.

In this paper, we provide an extensive analysis of the correlation between the weather and crime in Mexico, a warm country with high levels of crime. Our analysis is relevant to understand criminal behavior more generally because temperatures strongly and positively correlate with a wide variety of crimes, including thefts, injuries, homicides, and sexual crimes. Our main finding is that daily temperature is associated with changes in time use and higher alcohol consumption, which in turn are associated with higher crime rates on warmer days.

To the best of our knowledge, our work constitutes the first national-level evidence with modern econometric techniques on the role of time use and substance abuse in driving short-term crime rates. Changes in time use have been suspected to affect criminality at least since the late 1970s (Hindelang, Gottfredson, and Garofalo 1978; Cohen and Felson 1979). Time misuse, anti-social peer associations, and substance abuse are repeatedly observed among adolescents and young adults who become delinquents (e.g. Fergusson et al. 2002; Wasserman 2003; Osgood and Anderson 2004; Barnes et al. 2007; Heinz et al. 2011). However, a causal estimation of the impact of short-term changes in time use on crime has proven very difficult since quasi-experimental settings or natural experiments on time use are scarce.

We first characterize the association between temperature and crime with daily data on criminal charges. We rely on granular data of around 12 million daily crime rates at the municipality level over 16 years (1997–2012) across all of Mexico. Our model includes municipality by calendar day fixed effects, municipality by month and year fixed effects, and

* e.g., Kenrick and MacFarlane 1986; Anderson 1987; Reifman, Larrick, and Fein 1991; Auliciems and DiBartolo 1995; Anderson, Bushman, and Groom 1997; Horrocks and Menclova 2011; Ranson, 2014; Baysan et al. 2019.

date-specific (day, month, and year) fixed effects. We find a linear association between daily temperature and crime: for every increase in temperature by 1°C, the charge rate increases by 1.78 percent, even at comfortable temperatures. This association is stronger for violent crimes such as homicides, injuries, sexual crimes, and family violence. We also find that nearly 70 percent of crimes committed on hot days are offset by lower crime rates on the following days, possibly because crime could have decreasing returns (as suggested in Jacob, Lefgren and Moretti 2007). Nevertheless, increases in daily temperatures lead to a net surge in the total amount of registered crimes.

We also make a methodological contribution with several tests to gauge potential problems of sample selection. Temperature could influence the number of crimes being *recorded* and not necessarily the number of crimes being *committed*. This issue has not been thoroughly analyzed in the previous studies on temperature and crime, even though these studies have, for the most part, relied on administrative records and were therefore sensitive to sample selection.

The tests we perform in this paper imply that temperature has a genuine effect on criminal incidence. They also indicate that the factors that could be responsible for sample selection—for example, a change in victim reporting, evidence gathering, or police effectiveness—are not the primary reasons for the association between temperature and crime in our datasets. For instance, we show that relaxing the stringent municipality fixed effects of our econometric model has little impact on the results. This suggests that temperature conveys an effect on crime rates that is independent from the unobservables controlled for by our fixed effects, such as national-level daily shocks on crime reporting, evidence gathering, and police effectiveness. We also use victimization survey data that includes information on crimes that were not reported to the police. We find no evidence of an association between temperature and the probability that a crime is either reported to the police or investigated.

We then explore if the association between temperature and crime may be caused by shifts in time use. Graff Zivin and Neidell (2014) have shown that time use is sensitive to the weather in the U.S. Using Mexican time use surveys, we confirm this finding for Mexico and show that the time spent on multiple activities is influenced by temperature. We focus on two types of changes that we suspect could lead to surges in criminality: the time households spend outside of their homes and alcohol consumption.

Time spent outside of home is likely to increase the risk of being the victim of a crime because 86 percent of violent crimes happen outside of the victims' homes according to Mexican victimization survey data. Using Google Community Mobility Reports (Google LLC, 2021), we find that Mexican households spend less time in residential areas when the weather is warm. Satellite imagery of night-time light covering Mexico also indicate an increase in night-time activities during warm days. We then use the victimization survey data to show that there is an increase in the share of crimes happening outside of home on warm days. These results suggest that increases in temperature lead to more time spent outside which in turn might lead to more crime. Lastly, we find that the increases in crime caused by temperature are 40 percent higher on weekends compared to weekdays, i.e. when people have more flexibility to adapt their time use to the weather.

We furthermore find that alcohol consumption explains a significant share of the correlation between temperature and crime. For each additional Celsius degree, the average daily charge rate from offenders in "normal state" (i.e. sober) increases by 1.43 percent [1.19–1.67], while it increases by 3.69 percent [2.96–4.42] for drunk offenders. As a result, around 29 percent of all weather-induced crimes are committed by drunk offenders. We confirm that this is due to higher alcohol consumption on warmer days. We observe a positive correlation between alcohol consumption and temperature in Mexican Surveys of Health and Nutrition (2006, 2012 and 2018) as well as causal increases in alcohol purchases in Mexico following hot days. We corroborate these findings with alcohol consumption data from the U.S. Behavioral Risk Factor Surveillance System (2011-2019). In the U.S., we observe a positive association between alcohol consumption and temperature for the general population as well as the Hispanic population, of which 62 percent are of Mexican origin (Pew Research Center, 2019).

The remainder of this paper consists of three sections. Section I characterizes the association between temperature and crime. It includes a literature review (I.A), a data description (I.B), a description of our baseline model and results (I.C), an analysis of short-term dynamics (I.D) and tests for sample selection (I.E). Section II focuses on the contribution of time use to explain the association between the weather and crime. We show that time use correlates with the weather (II.A) and then focus on two types of changes in time use usually associated with higher criminality: the time spent outdoors (II.B) and alcohol consumption (II.C). Finally, the impact of temperature on weekends is reported in section II.D. Section III concludes.

I. The correlation between temperature and crime

I.A. Scientific literature on temperature and crime

Previous literature has found a correlation between high temperatures and crimes. One strand of the literature finds that extreme hot weather disrupts agriculture and the livelihood of low-income households, increasing the financial appeal to illegal activities and violence in the long term (Miguel 2005; Mehlum, Miguel, and Torvik 2006; Dell 2012; Iyer and Topalova 2014; Blakeslee and Fishman 2018). Another strand has found a strong correlation between high temperatures and crime in areas that do not depend on subsistence agriculture (e.g., Anderson 1987; and Ranson 2014 for the United States; Auliciems and DiBartolo 1995 for Australia; Horrocks and Menclova 2011 for New Zealand), suggesting that other drivers might also be at play.

The temperature–aggression relationship has been observed after only a short exposure to heat in a large array of situations (e.g., Reifman, Larrick, and Fein 1991, and Larrick et al 2011 in baseball matches; Kenrick and MacFarlane 1986 among car drivers), suggesting that high temperatures might consistently interfere with human behavior. The general idea is that high temperatures could reduce self-control or cognitive skills and that, under certain circumstances, this could lead to higher aggressiveness and crime. For instance, an empirical evaluation by Vrij, Van der Steen, and Koppelaar (1994) found that police officers training at high temperatures are affected by increased tension, a more negative impression of the offender, and aggressive behavior. While Anderson et al. (2000) found that the empirical evidence linking heat to aggression was mixed, more recent work suggests that a psychological channel is plausible. Baylis (2020) analyses one billion tweets in the United States and finds strong evidence of a sharp worsening of the tone of tweets when the temperature is above 70°F (21°C). Mukherjee and Sanders (2021) show that days with unsafe heat index increase violent interactions and the probability of violence among inmates of correctional facilities in Mississippi. In a laboratory setting, Almas et al. (2020) find that that thermal stress increases the willingness to destroy another person’s assets, even though this is only for a small subset of participants, and it could be context specific.

Several channels could explain the impact of temperature on crime concomitantly (Heilmann, Kahn and Tang, 2021). In particular, the probability of being caught may be different when an act is perpetrated during a cold day rather than a hot day, especially if the police are less efficient or active on hot days. Heilmann, Kahn and Tang (2021) analyze disaggregated data for the City of Los Angeles and find that, during very hot days, there is a decrease in the number of police stops but an increase in police investigations and arrests. In general, they do not find evidence that policing effort decreases under extreme heat. We are unaware of other studies showing that hot temperatures might enhance crime opportunities or decrease deterrence.

Another explanation is that temperature could affect time use, which in turn could affect crime. Time use has been found to be sensitive to changes in temperature (Graff Zivin and Neidell, 2014; Garg, Gibson and Sun, 2020). Thus, it is possible that potential victims may use their time differently during hot days (e.g., go out more), increasing their victimization risk. These weather-driven changes in time use could also affect substance and alcohol consumption by potential victims and criminals, which could lead to higher crime.

The time-use channel is supported by a large body of research linking time use and substance abuse to crime (e.g. Hindelang, Gottfredson, and Garofalo 1978; Cohen and Felson 1979, Fergusson et al. 2002; Wasserman 2003; Osgood and Anderson 2004; Barnes et al. 2007). However, it has not been analyzed thoroughly using modern econometric methods. In statistical analyses, Field (1992) interprets the correlation between warm days and criminality in the United Kingdom as caused by changes in activities but does not provide supporting quantitative evidence on time use. Heilmann, Kahn and Tang (2021), who focus on other channels for the impact of temperature on crime, also presume that there could be some effect of temperature on time use, although they do not quantify it. To exclude from their analysis the impact of temperature on arrests through changes in time use, they control for traffic flow when looking at the impact of temperature on traffic arrests.

Finally, existing empirical studies on the weather and crime are not exempt of statistical issues. A common problem is that the use of administrative data may misrepresent criminal incidence. For instance, if police effectiveness or police ability to gather evidence were a function of the weather, then temperatures could have an influence on crime data collection. Another recurrent problem when using judicial data, in particular from emerging countries where trust in institutions is low, is that victims systematically under-report crimes to authorities. It is a concern for the estimation of the temperature–crime relationship if people decide not to report a crime because temperatures are uncomfortable. The direction of the bias in this case is unknown. If victims reported fewer crimes on cold days, we would find that heat leads to higher crime rates than they do. In contrast, if victims reported fewer crimes on hot days, results could be attenuated.

These effects of sample selection might have confounded the results of earlier studies assessing the correlation between crime rate and temperature (e.g., Anderson 1987; Field 1992; Auliciems and DiBartolo 1995), but also the results from later research using similar administrative data (e.g., Ranson 2014; Blakeslee and Fishman 2018). In other datasets, sample selection may be less of a concern, but questions of external validity could remain.[†] Dealing with sample selection when using crime data is a problem that naturally goes beyond the strict analysis of the impact of the weather and crime. For instance, Jacob and Lefgren (2003) assess the impact of school calendars on juvenile crime and rely on administrative crime data from the U.S. National Incident-Based Reporting System. Their findings would be affected if changes in reporting were concomitant with school closure days.

I.B. Data

Crime data. Mexico is an interesting case to study because it records very high levels of criminality compared to other countries. Out of 97 countries, Mexico recorded the 4th highest rate of victims of intentional homicides per 100,000 inhabitants in 2020 according to the United Nations Office on Drugs and Crime (2022).

Our main crime datasets come from the Judicial Statistics on Penal Matters of Mexico published by the National Institute of Statistics and Geography (INEGI, 1997–2012). The dataset goes from 1997 to 2012 and it was discontinued after that date.

The data correspond to the administrative records of the Criminal Courts of First Instance (*Juzgados Penales de Primera Instancia*). These are the courts where the initial criminal charges are recorded, the criminals are prosecuted, and eventually sentenced by a judge. Our dataset contains information on charges, prosecutions, and convictions.

A charge is recorded in our dataset each time a judge drafts a resolution to decide whether a suspect should be kept in custody or released. In Mexico, each arrest has to be followed by such a resolution, usually within 72 hours of police custody even though special circumstances may allow for delays. The resolution is not always a resolution to keep the individual in prison since the judge can also dismiss the charges (if the evidence is insufficient) or order that the suspected offender is not kept in custody during the judicial process. Prosecutions include information on presumed criminals who have gone through a

[†] Baylis (2020), for instance, analyze the impact of temperature on mood with data from Twitter. To the best of our knowledge, this paper is the first to test for sample selection in the temperature-aggressiveness literature by looking at whether temperature induces a change in the composition of Twitter users. The results of Baylis (2020) do not seem to be driven by a change in the composition of users on hot versus cold days, and therefore robust to some form of sample selection. However, they are naturally limited in scope since the population of Twitter users does not fully represent the general or the offender population.

trial, and convictions are those found guilty. Therefore, the data on charges is recorded at an earlier stage and is more likely to include information on crimes for which nobody is sentenced. In this paper, we concentrate on charges because we are primarily interested in the occurrence of crimes. However, we also use the data on prosecutions and convictions to assess the judicial treatment of criminals.

The crime datasets contain detailed information on the type of crimes, the intentionality of the crimes, as well as the municipality, state, day, month, and year where and when the crimes took place. The datasets also include socioeconomic information on the person processed for a crime and the psychophysical status of the offender while committing the crime. We aggregate the data at municipality level.

The original datasets contain a wide range of over 400 detailed crime types which we have aggregated into broader crime categories. We also divide the overall and by-type number of crimes in each day by the yearly municipality population to compute daily criminal charge rates per million inhabitants. The population data come from the Mexican censuses of 1995, 2000, 2005, 2010, and 2020 (INEGI 1995, 2000, 2005, 2010, 2020). We perform a linear interpolation of the population for the years between two censuses to obtain estimates of the Mexican population in each municipality and each year.

We provide a table of summary statistics in **Appendix A**. The average daily charge rate in Mexico was around 5.75 charges per million inhabitants. The most common type of crime was theft (1.71 average daily charges per million inhabitants), followed by injuries (0.88) and property damage (0.48).[‡] Most crimes were intentional crimes.[§] There is a slight increase (by about 9 percent) in criminal offences over the weekend. In general, the average daily prosecution rate was about 28 percent lower than the average daily charge rate, and the average daily conviction rate about 36 percent lower.

We also use survey data from the Mexican National Surveys on Victimization and Perception of Public Safety (INEGI, 2011–2020). The main advantage of this dataset is that it includes crimes that were unreported to the police. Interviewees were asked if they were the victims of a crime, with information on the month and year when the crime occurred, as well as whether they reported the crime or not. We create victimization rates by place of residence using the survey weights. We also analyze answers to questions regarding the circumstances of crime

[‡] Injuries refer to any alteration in health and any damage that leaves a material mark on the body if those are caused by an external cause. They include but are not limited to wounds, abrasions, factures, dislocations, and burns.

[§] The terms come from the administrative records and correspond to a judicial interpretation of intentionality.

from the victim's perspective. These questions are not available in the administrative records of the Criminal Courts of First Instance. A main drawback of the SVPSS is that it only provides information on the month and year of occurrence of crimes.

Finally, we use the criminal investigation files of the General Attorney's Office of Mexico City (Fiscalía General de Justicia 2021) to assess the impact of temperature on crime at different times of the day. These files contain hourly data on reported crime (mostly after 2017) for the 16 municipalities that compose Mexico City.

Weather data. Mexico is also an interesting case to study because it is a large country that encompasses different types of climates. The central plateau, where Mexico City is located, provides a temperate climate. The North of Mexico is hot and arid, while most of the South is hot and humid.

We gathered daily temperature and precipitation data from the National Climatological Database of Mexico (CONAGUA 1996-2020). Records correspond to the data from around 5,500 operating and formerly operating land-based stations in Mexico. However, the data have been aggregated at municipality level to match the criminality data. We match the municipalities in Mexico with the closest land-based weather stations.[**] Following recommendations by the World Meteorological Organization (2011), we compute the daily average temperature as the average between the maximum and the minimum temperature of a given day.

We provide the historical distribution of daily average temperatures in Mexico from 1997 to 2012 in **Appendix A**. We constructed 13 temperature bins: the "less than 10°C" bin is the lowest, the "more than 32°C" bin the highest, and there are eleven 2°C bins between them. The climate in Mexico is hotter than most countries. Days where the average temperature is between 16°C and 18°C are the most frequent, and the daily mean temperature oscillates between 14°C and 22°C during more than half of the year. At the extremes of the distribution, there are 5.44 days per year below 10°C (50°F) and 2.49 days above 32°C (90°F) on average.

The data we obtained from CONAGUA does not include the most recent dates for all municipalities, especially after 2017 due to strong delays in reporting and validation. In some analyses, we need more recent weather data. In this case, we use the weather data from the

[**] We consider a land-based weather station to be within a municipality if it is less than 20km from its centroid. For municipalities that are isolated, we may have fewer than five active stations in the 20km radius. In this case, we match each municipality with the five closest stations within a maximum radius of 50km. Once we have identified the land-based stations relevant to a municipality, we compute the daily mean temperature and precipitation levels in a municipality by averaging the records of all the stations relevant to a given municipality. The longitude and latitude of Mexican municipalities is obtained from INEGI (2021).

Climate Predictions Centre (2003–2021). This dataset has more recent observations but only a 0.5° by 0.5° resolution (around 55km by 55km), and it is therefore less precise than the data from land-based stations. We calculate the centroid of each municipality, and then match it with the closest data point in the gridded weather data. The CPC data (2003–2021) also covers the U.S. This is another reason to use this dataset because we perform a few robustness checks with U.S. data.

Additional data sources. We use several complementary data sources. We look at the correlation between the weather and time use with the Mexican Surveys on Time Use (INEGI, 2009, 2014 and 2019), and corroborate the findings for Mexico with U.S. data from the American Time Use Surveys (U.S. Bureau of Labor Statistics, 2003-2019). We also look at nighttime activities with daily night-time light data with NASA satellite imagery covering Mexico since January 2012 (Roman et al., 2018), and look at changes in people's location with Community Mobility Reports (Google LLC, 2021) that rely on the location of the smartphones of its users. Moreover, we study alcohol consumption patterns with data on alcohol consumption from the Mexican Surveys of Health and Nutrition (NIPH, 2006, 2012; INEGI and NIPH, 2018 and 2018b); alcohol purchases from the Mexican Surveys of Household Income and Expenditure (ENIGH in Spanish) (INEGI, 2012, 2014, 2016, 2018); data from Google trends (Google LLC, 2004-2019) on online search interest for the topic "alcoholic beverages"; and corroborate findings with U.S. data from the Behavioral Rick Factor Surveillance System (CDC, 2011-2019). We also refer to information from the 2008 Mexican National Addictions Survey (SSA, 2009). Finally, we extract information about the use of air-conditioning (AC) from the ENIGH (INEGI, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012) and the 2018 National Survey on the Consumption of Energy Sources in Private Housing Units (INEGI, 2018).

I.C. Main model and results

Our baseline model correlates the daily charge records with the temperatures of the days when the crimes occurred. Performing the analysis at daily level allows us to focus on the non-economic determinants of crime. Daily records ensure the correct identification of the causal effect of temperature on charges in the short run while maintaining constant different socioeconomic factors influencing criminal behavior such as income, social inequities, or the effectiveness of the legal system. Our baseline model is as follows:

$$(1) \qquad Y_{i,d,m,t} = \theta . T_{i,d,m,t} + \mu_{1,i,d,m} + \mu_{2,i,m,t} + \mu_{3,d,m,t} + \varepsilon_{i,d,m,t},$$

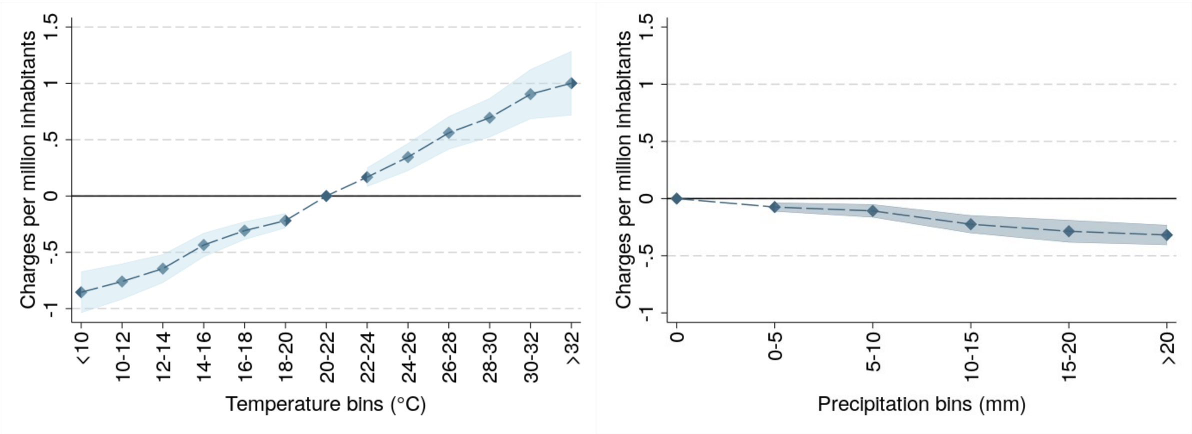
where $Y_{i,d,m,t}$ is the charge rate of municipality *i* on day *d* of month *m* and year *t*. θ is a vector of parameters. $T_{i,d,m,t}$ is a vector of climatic variables that we discuss in detail below.

In Eq. (1), we use three types of fixed effects. $\mu_{1,i,d,m}$ is a municipality by calendar day fixed effect, controlling for the average crime rate in municipality *i* in each day *d* and month *m*. This allows us to fully control for seasonality at municipality level. We identify the effect of the weather on crime by comparing differences in charge rates for each municipality and calendar day across different months and years. When doing this comparison, we control for the average difference in charge rates in municipality *i* from one month to the other with municipality by month and year fixed effects (denoted $\mu_{2,i,m,t}$). We also include date-specific time fixed effects ($\mu_{3,d,m,t}$) to control for nation-wide differences in charge rates on any given day.

The vector $T_{i,d,m,t}$ includes our climatic variables of interest. To assess the non-linearity in the charge–temperature relationship, the most conservative approach is to use temperature bins to specify the relationship between temperature and charge rates. This approach has been done in other applications, such as mortality and energy demand (e.g. Deschenes and Greenstone 2011; Cohen and Dechezleprêtre, 2022). The model requires as many dummy variables in $T_{i,d,m,t}$ as temperature bins, each taking the value of 1 when the day's temperature falls within the range of the respective bin. We use 2°C temperature bins (e.g., 10–12°C, 12–14°C) to construct the vector $T_{i,d,m,t}$. The lowest bin covers days with temperature below 10°C, and the highest bin covers days with temperature above 32°C. The vector $T_{i,d,m,t}$ also includes information on precipitations. We resort to six precipitations bins to account for non-linearities in the crime–rainfall relationship: no rain, 0–5mm, 5–10mm, 10–15mm, 15–20mm, and above 20mm. In some specifications and for some calculations, we use continuous variables rather than temperature bins. That is, we use the average daily temperature and total precipitations in municipality *i* and day *d* as the main variables of interest in $T_{i,d,m,t}$. In our econometric estimations, we account for heteroskedasticity by computing cluster-robust standard errors. Each cluster corresponds to a given municipality. We use the population of each municipality as a weight to obtain coefficient estimates that are representative of the population.

The general results obtained from Eq. (1) are reported in **Figure 1**. On the left panel, we provide the results for temperature. The daily charge rate per million inhabitants is shown on the y-axis and the temperature bins on the x-axis. We find a linear relationship between the average daily temperature and charge rates. Using the daily average temperature as the independent variable of interest instead of the temperature bins, we compute that an increase by 1°C is associated with an increase in the daily charge rate of 0.102 crime per million inhabitants.[††] This corresponds to a 1.78 percent increase per °C in the average charge rate. **Figure 1** shows that the difference between a cold day (above 10°C) and a hot day (below 32°C) is sizeable: it corresponds to an increase of 1.85 daily charges per million inhabitants, roughly equal to 32 percent of the average daily charge rate. On the right panel of **Figure 1**, we provide the results for precipitations. We find that high levels of precipitation (>20mm in a day) reduce overall criminality by around 0.32 charges per million inhabitants. This represents around 5.5 percent of the average daily charge rate in Mexico. In **Figure 2**, we break down our analysis with separate regressions by type of crime. To ease comparability, each graph has been normalized based on the average charge rate observed in the data for each type of crime. Thus, the y-axis represents the percentage change with respect to the average charge rate for that crime.

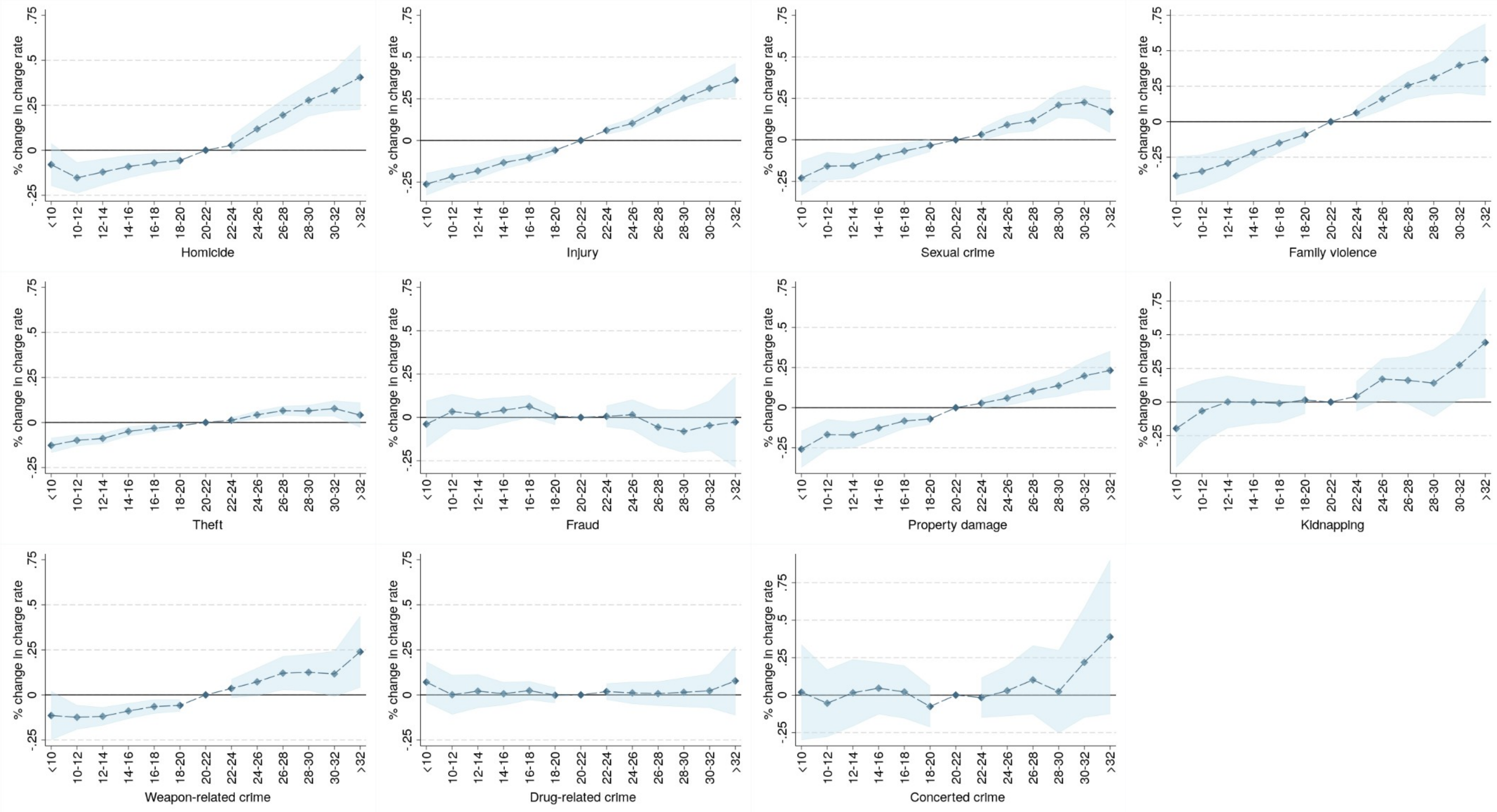
Figure 1. Daily correlation between charges and the weather (all crimes)



Notes: The two panels correspond to the results of our baseline model. The dependent variable measured in the y-axis is the daily charge rate (all crimes) in crimes per million inhabitants. In the left panel, we report the results for all the temperature bins (on the x-axis). In the right panel, we report the results for the precipitation bins included in the baseline specification. 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. 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 and 0mm for precipitation.

[††] The regression results are provided in **Table 1**.

Figure 2. Correlation between on-the-day temperature and daily charge rates by type of crime



Notes: Each graph corresponds to a separate regression. The dependent variable is the daily charge rate per million inhabitants, normalized on the y-axis according to the average charge rate of 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 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. 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 and 0mm for precipitation.

Figure 2 shows that charges for violent crimes (homicide, injury, sexual crime, family violence, weapon-related crime, damages to property, and kidnappings) have the strongest correlations with hot weather: the average charge rate during unusually hot days (>32°C) is higher by around 50 percent compared to unusually cold days (<10°C). We also find a positive association between temperatures and thefts, but the magnitude is smaller. We find no correlation with frauds, drug-related crimes, or concerted crimes. This is not particularly surprising considering that these crimes tend to require more preparation and planning.

In **Appendix B**, we provide several additional analyses and robustness checks to characterize the association between temperature and crime in Mexico. For instance, we run fixed effect Poisson regressions to account for the present of zero values in the dependent variable. Results are very similar. We break down the correlation between temperature and crime by gender and age of the suspected offenders. We find that younger offenders are as sensitive to temperature as older offenders. Since an agricultural channel was identified for the long-term correlation between temperature and violence, we also provide results for agricultural workers to look at difference due to short-term exposure**.** Our results suggest that the proportion of agricultural workers being suspected of a criminal offense is stable across the temperature range. Other analyses in **Appendix B** include a separate analysis of the impact of temperature before and after 2006, rural and urban areas, and maximum and minimum temperatures. Davis and Gertler (2015) show that air conditioning (AC) in Mexico varies widely across the country. Thus, we also consider 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 are not causal and could be confounded by other differences across Mexican States apart from different levels of AC penetration.

I.D. Additionality of weather-induced crime

Jacob, Lefgren and Moretti (2007) use U.S. weather and crime data to show that weeks with higher-than-average crime rates are followed by weeks with below-average crime rates, particularly for violent and property crime. A similar effect for Mexico can be observed with our data. We can show that the peaks in crime on hot days, as displayed in **Figures 1 and 2**, are largely offset by lower crime rates on the following days. However, the results in this subsection suggest that some crimes are additional indicating that there is a genuine impact of temperature on the occurrence of crimes.

Consider the following equation, which includes distributed lags for the effect of the weather of the previous days on the crime rate of day *d*:

(2) $$Y_{i,d,m,t} = \sum_{k=0}^{K} \sum_{s} \theta_{s,-k} . T_{s,i,d-k,m,t} + \mu_{1,i,d,m} + \mu_{2,i,t} + \mu_{3,d,m,t} + \varepsilon_{i,d,m,t},$$

where K stands for the number of lags for the weather variables included in the model. We use $K=14$ after checking that results are stable with larger values. The subscript *s* stands for the weather variables included in the model, and $T_{s,d-k,i}$ corresponds to the value of each variable *s* on day (*d*-*k*), month *m*, year *t*, and in municipality *i*.

In **Table 1**, we compare the results of a model with no distributed lags (column 1) and a model with distributed lags (column 2, consistent with Eq. 2). For concision, rather than using different temperature and precipitation bins, we use the average temperature and total precipitation and their lags.

Table 1. Correlation between the weather and the charge rate with and without distributed lags

	Without distributed lags (1)	With distributed lags (2)
Average daily temperature (in °C):		
Effect on the day	0.102***	0.108***
	(0.0063)	(0.0074)
First lag		-0.0072
		(0.0079)
All other lags (2-14 days before)		-0.0678***
		(0.0136)
Total effect		0.0329**
		(0.0161)
Total daily precipitations (in mm):		
Effect on the day	-0.0093***	-0.0083***
	(0.001)	(0.0011)
First lag		-0.007***
		(0.0011)
All other lags (2-14 days before)		-0.0012
		(0.0038)
Total effect		-0.0164***
		(0.0041)

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) only includes average daily temperature and total daily precipitations as explanatory variables. The model of column (2) also includes 14 lags for temperature and 14 lags for precipitations on the previous days. The rows for "All other lags (2–14 days before)" display the cumulative effect of all 13 lags from the 2nd to the 14th lag. The rows for the "total effect" report the cumulative effect of the coefficients on the day and for the 14 lags. 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.

Table 1 shows that the coefficients for the on-the-day impacts of temperature and precipitation are very similar in both columns and, therefore, not influenced by the inclusion of the temperature and precipitation lags in column (2). Therefore, we can disregard the effect of temperature and precipitation lags when only interested in the immediate response of crime to temperatures or precipitations.

However, while the coefficients for the temperature lags are not statistically significant when taken individually, they are systematically below zero. When added together, these lags strongly attenuate the effect of temperature on the charge rate. We find that the cumulative effect of 1°C after 14 days is equal to a 0.033-point increase in the charge rate [95 confidence interval is 0.002–0.065]. In relative terms, this means that a 1°C increase leads to a 0.57 percent increase in the charge rate. The difference between a cold day at 10°C and a hot day at 32°C is therefore equivalent to an increase of around 12.6 percent in the charge rate. While this effect remains strong, it is 68 percent lower than the effect recorded with a model without distributed lags. Therefore, slightly more than 30 percent of temperature-induced crimes are truly additional. The rest are displaced crimes that happened on hot days but would have happened anyway. Jacob, Lefgren, and Moretti (2007) suggest that this displacement effect could be a result of the decreasing marginal utility of crime over time. The same explanation is plausible in our case.

In contrast, for precipitation we show that cumulative effects are stronger than contemporaneous effects. The first precipitation lag conveys nearly the same effect on the charge rate as the contemporaneous level of precipitation. We believe this is because expectations of rain may have an equally important effect on the charge rate than actual realizations of rain.

We provide a few robustness checks on short-term dynamics in **Appendix C** including separate results with different number of lags, results with leads and by type of crime. We also use the exact same specification as Jacob, Lefgren and Moretti (2007) to look at displacement effects. Results are similar but rely on an Instrumental Variable (IV) strategy which is unlikely to hold with our data. This is why we prefer the specification and results of **Table 1**.[‡‡]

In the remainder of this paper, we use a model without distributed lags since we want to focus on the mechanisms behind the immediate correlation between temperature and crime, independently from whether these crimes are truly additional or not.

[‡‡] We also analyze 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 concision.

I.E. Sample selection.

Because we only have information for the crimes that are recorded in the data, any change in how charges were recorded may bias the observed correlation. Thus, our results could be misleading due to a sample selection bias if the weather correlates with either crime reporting, police effectiveness, or evidence gathering.[§§] A corollary is that evidence of sample selection, or the absence of evidence of sample selection, can inform us about the role that changes in deterrence and reporting may play as potential drivers of the temperature–crime relationship.

Hereafter, we perform several tests to assess the plausibility that our results for charges are biased due to sample selection. We use victimization data which includes information on reported and unreported crimes. **Table 2** provides the correlation between monthly temperature and the monthly victimization rates by place of residence[***] as recorded in the SVPPS surveys on victimization. Column 1 shows the correlation for all declared incidents. Columns 2–4 provide a breakdown by type of incidents recorded in the victimization data: thefts (46.8 percent of incidents), threats (27.6 percent of incidents), and a group of crimes gathering the majority of the most serious incidents (including injuries, kidnapping, and sexual crimes that comprise 6.8 percent of incidents). We grouped these serious crimes together because these categories recorded few crimes separately.

In **Table 2** column 1, we observe a positive association between temperature and all victimization incidents reported in the survey data. Correlations with temperature and each type of incidents are positive for all categories. Correlations are similar in magnitude compared to the charges data, with about a 1.6 to a 1.9 percent relative increase in the dependent variable for every Celsius degree.[†††]

Table 2. Correlation between the weather and victimization rates in survey data

[§§] Because our main dataset is about charges, only the forms of evidence gathering that happen before potential offenders are charged may create issues of sample selection. When a crime is reported, the police may decide to undertake an investigation or not. They may finally proceed with an arrest if they find a suspect or a group of suspects. They will have to justify this arrest to a judge, who will emit a resolution. If this process is sensitive to temperature, then our results could be biased. In contrast, our results would not be subject to sample selection if evidence gathering was affected by the temperature on the day of the crime later down the line in the judicial process.

[***] We use the place of residence and not the place of occurrence to compute rates with the survey data. This is because we need to divide the crime counts by a relevant population count, and since the data is a survey, there is an imbalance between the number of crimes that happen in the surveyed areas and outside the surveyed areas. Therefore, crime rates are only comparable when dividing the number of crimes affecting the residents of an area by the population in a surveyed area.

[†††] Numbers are larger in **Table 2** since rates are monthly, not daily, and the survey data encompasses unreported crimes whose severity is likely to differ from the crimes in the charges data.

	All incidents	Thefts	Threats	Injuries, kidnappings, and sexual crimes
Average monthly temperature(°C)	465.1***	250.5***	130.7***	43.1*
	(91.6)	(49.7)	(39.0)	(22.2)
Total monthly precipitations (mm)	-79.3	-43.6	-14.4	-24.4
	(52.8)	(26.8)	(32)	(15.1)
Impact of 1°C relative to sample average	1.74%***	1.94%***	1.63%***	1.89%*
	(0.34%)	(0.39%)	(0.49%)	(0.97%)

Notes: Each column corresponds to a separate regression. The dependent variables are different in each column, but all are measured in crimes per million inhabitants per month. All models include the average monthly temperature and total monthly precipitations as explanatory variables. Regressions include municipality fixed effects and month by year fixed effects. The last column 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. 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.

The SVPPS data also includes two closed-ended questions related to whether a crime was reported or a preliminary inquiry was filed (conditional on a crime being reported). We check if ambient temperatures correlate with the answers to these questions. We run logistic models to assess the probability of a positive answer to each survey question as a function of the average monthly temperature (for month *m* and year *y*) in the municipality where the crime occurred.[‡‡‡] The answers to each question could depend on the victim's identity, the crime type, and the offender's identity. We therefore control for these elements to assess the impact of temperature on reporting for similar crimes (control variables are fully described in the notes below **Table 3**). We use the recommended survey weights to ensure that crimes are nationally representative and cluster standard errors at the municipality level. Results for all crimes and by crime type are displayed in **Table 3**. We observe no statistically significant correlation between temperature and whether a crime is reported by the victim or investigated with a preliminary enquiry.

[‡‡‡] In this case, we can use the place of occurrence because we do not need to normalize results by the population in each municipality. This is because we directly use a logistic model to predict positive answers and we do not compute victimization rates.

Table 3. Impact of average monthly temperature on victim reporting and police enquiries

	All	Thefts	Threats	Injuries, kidnappings, and sexual crimes
Crime reported	-0.003	-0.002	0.005	0.002
	(0.012)	(0.015)	(0.025)	(0.025)
Preliminary enquiry (if crime reported)	-0.023	-0.033	-0.035	-0.065
	(0.021)	(0.028)	(0.043)	(0.065)

Notes: Results from logistic models. Each cell provides the result of a separate regression (for a different question and type of crime). Models 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); fixed effects for the age range of the offender; if they acted alone, their gender (with a value of 2 for men, 1 if there was an equal amount of men and women, 0 for women); and if the offender carried a weapon. We also include monthly total precipitations as an additional control variable. All models are weighted by survey weights. Standard errors are in parenthesis and clustered at the municipality level.

In **Appendix D**, we report additional tests of sample selection for the interested reader. Because our baseline econometric specification includes many fixed effects, Eq. (1) controls for some forms of sample selection. For instance, Eq. (1) controls for differences in reporting from one month to the other. By removing fixed effects, we can assess if results are stable. Moreover, this allows us to identify if there are significant associations between the weather and the differences controlled by the fixed effects, especially changes in evidence gathering, police effectiveness, and reporting. This is because sample selection bias is essentially an omitted variable bias (Heckman 1976) that can be corrected by controlling for the probability of selection into the sample. We find 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 strongly correlate with the weather in a way that would invalidate our results.

In **Appendix D**, we also compare the data on charges with those on prosecutions and convictions. We show that the proportion of unintentional crimes (as classified by the police: e.g., car accidents and manslaughter) 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. We finally show that, conditional on a crime being undertaken, failed attempts are about 1 percent 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. Criminals are in fact failing more often on hot days.

In summary, our tests for sample selection coincide. They suggest that sample selection due to reporting, evidence gathering, and police effectiveness is not the main driver of the correlation between crime and temperature shown in **Figures 1 and 2**.

This is a reasonable finding since cold or warm temperatures are not a very plausible reason not to report a crime. The people that report crimes in Mexico go through a long list of hurdles, and the reasons not to report a crime tend to be serious.[§§§] Likewise, because reporting a crime is an effort and the police has limited means, the crimes that are recorded by the police tend to be serious crimes, and it is rather unlikely that a serious crime such as a murder, injury, or theft with violence would not be reported or investigated because of outside temperatures. For homicides, we can compare our results with those of Garg, McCord, and Montfort (2020), who look at the correlation between homicides and on-the-day temperature, using data from the Mexican death statistics. They find that a 1°C increase in temperature amounts to a 2.1 percent increase in daily homicide risk. This is very similar to our findings for homicides: the results of **Figure 2** are equivalent to a 2.6 percent [1.8–3.4] increase in homicides for every Celsius degree. Since mortality data are subject to less under-reporting than judicial data, finding similar effects across both datasets suggests that there is no bias caused by an association between temperature and homicide data collection in our charges dataset.

Finally, within the comfort zone of the human body, changes in police effectiveness or changes in people's willingness to report a crime would naturally be less likely to explain changes in reported crime because there is barely any change in comfort for police to operate or people to report a crime. Sample selection is therefore much less likely to bias our results near 20°C temperatures. Likewise, physiological effects linking temperature to violence are highly unlikely to operate at comfortable temperatures. This is a feature that we exploit later in the text to isolate potential impacts due to changes in time use from physiological or sample selection effects.

II. Time use, the weather and crime

In the remainder of this paper, we explore if temperatures could have a strong influence on time use, and if these changes in time use could explain the changes in crime rates that we observe in **Figures 1 and 2**.

[§§§] In the SVPPS 2016 , 37% of victims say that they did not report crimes for major reasons such as lack of evidence (10.6%), fear of retaliation (6.8%), distrust of authorities (16.3%), or a hostile attitude from authorities (3.3%).

II.A. Influence of the weather on time use

Previous work has found statistical evidence of an association between time use and weather in the United States (Graff Zivin and Neidell 2014) and China (Garg, Gibson and Sun, 2020). We provide evidence for Mexico using the 2009, 2014 and 2019 Mexican surveys on time use (INEGI 2009, 2014, 2019). These surveys contain around 156,000 time-use observations in total from people interviewed over 47 days in 2009 and 60 days in 2014 and in 2019. We use the following model:

(3) $$TU_{z,i,d,m,t} = a\, NT_{i,W(d),m,t} + u_i + g_d + \lambda_{n(z)} + \omega_{z,i,d,m,t}$$

where $TU_{z,i,d,m,t}$ is the average time spent daily (in minutes) in a given activity by respondent *z* in municipality *i* during the week before the interview. The subscripts *d*, *m* and *t* correspond to the day, month and year of interview. We provide information for the following categories of activities, and therefore run separate regressions for each of them: (1) work and work-related commute; (2) studying, homework and commute to study; (3) socializing, relaxing and leisure; (4) sports, exercise and recreation; (5) religious and spiritual activities; (6) eating and drinking; and (7) sleeping.[****]

The vector $NT_{i,W(d),m,t}$ consists of climate variables that includes the average daily temperature and precipitations recorded on the week (denoted *W(d)*) prior to the interview in the municipality where the interview took place. u_i is a municipality fixed effect and g_d is a date fixed effect (day, month and year). We also create groups of respondents, denoted $n(z)$, based on their age and gender. We then include group fixed effects, denoted $\lambda_{n(z)}$, to control for the impact of age and gender on time use. $\omega_{z,i,d,m,t}$ is the error term.

The National Surveys on Time Use for 2009, 2014 and 2019 include weights that allow us to calibrate the model according to the probability of selection into the sample. We use these weights to make sure that we report effects that are representative of the Mexican population. Finally, for each respondent, we compute the total amount of time declared in any activity. Ideally, this amount should be equal to the 10,080 minutes contained in a week, but some people report total amounts well below or well above. We exclude from the analysis the 5

[****] Working time includes commuting for work purposes. Studying time includes homework and research as well as commuting to study. Socialising, relaxing and leisure time includes: cultural or artistic activities; playing board games, betting games or videogames; going to the park, cinema, fairs, stadiums, museums or other cultural sites or of entertainment; spending time speaking with other household members; attend parties, the visit of family members, friends and acquaintances; watching television; listening to the radio or using any other audio appliance; checking emails or social networks; looking for information on the internet; reading a book, journal, or any other material.

percent of respondents with lowest total amount of time spent in all activities, and the 5 percent of respondents with highest amount of time spent in all activities. We also include only those respondents that declare spending at least one minute on the activity of interest in the estimation samples. This is done to reduce measurement errors since some respondents could have forgotten to declare spending time on an activity of interest.

The correlations between the weather and time use based on the Mexican surveys on time use are reported in **Table 4**. The first column provides the average time spent daily on these activities in the estimation samples. The other columns provide the estimation results. We find that, at higher temperatures, respondents spend less time working and commuting to work or studying and commuting to their place of study. A 1°C increase in temperature reduces working time by 0.26 percent, and study time by 0.31 percent. Therefore, on a day at 30°C, the people in the samples tend to work and commute to work about 5 percent less; and study and commute to study about 6 percent less compared to a day at 10°C. We also find that respondents spent less time at social events and relaxing (for instance, watching TV, using social media, etc.); or eating and drinking when the temperature increases. The results in **Table 4** also suggest that other activities may increase with temperature, for instance working out (even though the coefficient is not statistically significant), religious and spiritual activities (the coefficient is positive and statistically significant), or sleeping (not statistically significant).

Complementary analyses for the impact of the weather on time use are provided in **Appendix E**. We find evidence of possible non-linearities in the relationship between time use and temperature, especially at the extremes. For instance, time spent working out may decrease during heat waves (with average temperatures above 30°C). Besides, 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**, we use the American Time Use Survey (ATUS) (U.S. Bureau of Labor Statistics, 2003-2019). The 2003-2019 ATUS data files include information from more than 200,000 interviews in the United States. 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 most of the activities in both the U.S. and the Mexican data. Six of the seven categories of activities analysed have a similar sign for temperature in the Mexican data and for the Hispanic population of the U.S.

Table 4. Correlation between the weather and time use in Mexico

Activities	Average time spent daily (in min)	Effect of temperature (in °C)	Effect of precipitations (in mm)
Work and work-related commute	432	-1.13***	-0.21
		(0.41)	(0.31)
Studying, homework and commute to study	340	-1.07***	0.15
		(0.38)	(0.28)
Socializing, relaxing and leisure	171	-1.07***	-0.59**
		(0.33)	(0.24)
Sports, exercise and recreation	40	0.14	-0.05
		(0.09)	(0.08)
Religious and spiritual activities	22	0.42***	0.11
		(0.10)	(0.08)
Sleeping	460	0.22	0.21
		(0.18)	(0.14)
Eating and drinking	70	-0.90***	-0.09
		(0.12)	(0.06)

Notes: The first column is for the average time spent in each activity in the sample. This is after dropping outliers and respondents with no time spent recorded on the dependent variable (as explained in the main text). The other two columns are regression results. The results in each row correspond to different regressions. The results for precipitations are taken from the same regression as the results for temperature. 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 of the surveys. Temperature and precipitations correspond to the average daily value during the week of reference. The weather data used is the CPC gridded weather data. ***p<0.01, ** p<0.05 and *p<0.1.

The above analyses suggest that temperature influences the time spent on all sorts of activities. Therefore, temperature could have an impact on victimization risks and criminal activities through changes in time use.

Hereafter, we focus on two types of changes typically associated with criminality: (1) the amount of time that victims spend outside of home; and (2) alcohol consumption. We furthermore look at the difference in the association between temperature and crime on weekdays and weekends. This comparison is relevant because households are likely to have more flexibility to adapt their schedules to the weather on weekends when they are less constrained by work obligations.

II.B. Influence on victimization risk outside of home

Time use is likely to have an influence on victimization risks because the probability of being confronted with a crime depends on where people are located and, therefore, on how they spend their time (Cohen and Felson 1979). According to the Mexican victimization survey data, about 64 percent of incidents happen outside of home, especially in the street (about 34 percent of all incidents) or in public transport (about 11 percent of incidents). In the case of violent crimes (injuries, sexual crimes, and kidnappings), about 86 percent happen outside of home.

The time use surveys in Mexico do not separate activities by location. However, since the start of the COVID-19 pandemic in 2020, Google has published Community Mobility Reports (Google LLC, 2021) based on the location of the smartphones of its users. The Google data for Mexico is at the state level. The dataset provides daily information on the frequency of visits to six categories of areas.[††††] We correlate this frequency data by area with the population-weighted average daily temperature and precipitation in each Mexican state. The results in **Table 5** show that the frequency of use of residential areas is decreasing in temperature and increasing in precipitations. In contrast, the frequency of visits in all other places (i.e., outside home) increases under warmer weather and decreases when it rains. The frequency of parks visits seems particularly weather sensitive.[‡‡‡‡]

Table 5. Weather and changes in the frequency visits in Mexico using Google Community Mobility Reports.

	Percent change compared to Google baseline					
	Residential	Workplace	Transit stations	Grocery and pharmacy	Retail and recreation	Parks
Daily temperature (°C)	-0.087***	0.175***	0.232***	0.007	0.068	0.326***
	(0.015)	(0.065)	(0.073)	(0.079)	(0.059)	(0.081)
Daily precipitations (mm)	0.036***	-0.073***	-0.072***	-0.068**	-0.081***	-0.124***
	(0.007)	(0.022)	(0.018)	(0.028)	(0.021)	(0.022)

Notes: Each column corresponds to a separate regression for a type of area (e.g., parks). The dependent variables, as provided by Google, are the percentage change in frequentation in the type of area relative to a baseline. This baseline (not disclosed by Google) is equal to the median observed value, for the corresponding day of the week, during the 5-week pre-pandemic period (between January 3rd and February 6th, 2020). The Google data was downloaded on November 19th, 2021, and includes observations from January 1st, 2021, until November 16th, 2021. Our regressions include state by week fixed effects to control for seasonality as well as sudden regional changes in COVID-19 policies that might correlate with the weather and affect time use (especially social distancing policies). We furthermore use date fixed effects (day, month, and week). The weather data used in these models 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.

The results from **Table 5** suggest that under warm weather, people may spend more time in locations associated with higher victimization risk. In **Table 6**, we show corroborating evidence using the Mexican victimization surveys. In particular, we find that higher temperature is associated with a reduction in the share of incidents happening at home and,

[††††]

[‡‡‡‡] Unfortunately, results may lack some external validity to understand pre-pandemic mobility. Especially, the information on workplaces should be interpreted with caution because workplace practices changed with the pandemic, with more and more people working from home. The positive coefficient for temperatures in the case of "workplaces" could therefore display a preference to work in the office rather than working from home on warmer and drier days (and not a strict preference to work on warmer days). For other categories, **Table 5** is likely to provide insightful information on a general preference to spend less time at home and plausibly more time outdoors (e.g., in parks) on warmer and drier days.

therefore, with an increase in the share happening elsewhere. This reduction comes from direct altercations (threats, injuries, kidnappings, and sexual crimes) but not from thefts. This is plausible since absences from home could lead to additional burglaries.

Table 6. Impact of average monthly temperature (°C) on the share of incidents happening at home

	All	Thefts	Threats	Injuries, kidnappings and sexual crimes
Incident happened at home	-0.036***	0.029	-0.032**	-0.08***
	(0.013)	(0.041)	(0.013)	(0.028)

Notes: Results from logistic regressions. The dependent variable is whether the crime happened at home (value of 1) or elsewhere (value of 0). Each column provides the result of a separate regression (for a different type of crime). Models 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 2 for men, 1 if there was an equal amount of men and women, 0 for women); and if the offender carried a weapon. We also include monthly total precipitations as an additional control variable. All models are weighted by survey weights. Standard errors are in parenthesis and clustered at municipality level. ***p<0.01, ** p<0.05, and *p<0.1.

Appendix F provides additional evidence on time use and victimization risks during hot days. We confirm our results regarding the time households spend away from home with data from the American Time Use Surveys. U.S. respondents spend less time at home on warm days. We also find that households spend more time outdoors away from home, especially between 6pm and 12pm. This is often nighttime since the sun generally sets between 6pm and 8pm (this varies according to the season and time zone). We do not have similar information for Mexico. However, we use night-time light data from NASA (Roman et al. 2018). In **Appendix F** we show that night-time light in Mexico is positively correlated with temperature. While we cannot describe which specific activities are associated with more night-time light (some of them could be industrial activities), this result suggests that increases in night-time activities correlate with higher temperatures in Mexico.

The criminal investigation files (*Fiscalía General de Justicia 2021*) of Mexico City provide information on the hour when crimes are committed. Conditional on a crime taking place, we estimate the probability that it occurred at a specific moment of the day as a function of temperature. Under warm weather, we observe an increase in the share of crimes committed in the late afternoon and at night (from 6pm to 6am) (see full results in **Appendix F**). This change in the timing of crimes suggest that exposure to crime might increase especially at night. Interestingly, the coolest hours of the day seem to be those that drive criminality on warm days. This could 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.

We can consider two complementary channels to explain the impact of time use on crime. First of all, the way potential victims use their time may affect their exposure to crime. In addition, the way criminals use their time may also affect crime rates. The impact of time use on crime is likely to stem from both. To better understand the contribution of the second mechanism, it is useful to focus on crimes that do not require a victim to be present. Our victimization survey data records whether respondents were victims of "wall paintings or graffiti on [their] house, intentional scratches on [their] vehicle or any other type of vandalism". This category is interesting because these incidents happen in the absence of the victim, and are easier to execute. Compared to a burglary that requires preparation, it is relatively easy to find a car or a wall that is not under surveillance. We can therefore cautiously presume that these crimes are mostly driven by how offenders might use their time. In **Appendix F**, we show that there is a positive and statistically significant correlation between these acts of vandalism and temperature. We also find an association (statistically significant at 10 percent) between temperature and vandalism within a reasonable temperature range (18°C to 23°C). This is relevant because physiological effects and sample selection biases are less likely to drive the results at mild temperatures. This last analysis suggests that offenders may prefer to commit some criminal activities at warmer temperature levels, independently of what victims might do.

II.C. Alcohol consumption, temperature and crime.

Alcohol consumption is well known to have an impact on aggressiveness, disinhibition, and crime. For instance, Heinz et al (2011) estimates alcohol is implicated in about 50 percent of all violent crimes and sexual assaults in developed countries. Biderman, De Mello and Scheneider (2017) show that dry laws in Sao Paulo, Brazil, caused a drop in homicides and battery. Chalfin, Hansen and Ryley (2019) find that the consumption of alcohol increases the victimization risk for violent and property crime. Other works have shown higher crime from lowering the minimum legal drinking age and a correlation between crime and the number of establishments with alcohol licenses (Christopher and Dobkin, 2011; Kypri et al. 2014).

In this subsection, we first provide evidence that alcohol consumption increases with temperature. We then look at the association between temperature, crime and alcohol consumption with the crime data.

Alcohol consumption and temperature. The National Institute of Public Health (NIPH) conducted National Surveys of Health and Nutrition in Mexico (NIPH, 2006, 2012; INEGI and NIPH, 2018 and 2018b) where they asked respondents to provide detailed information on eating and drinking behaviour over the past 7 days, covering more than 100 items.

We use these records to assess the correlation between the weather and the declared alcohol intake for about 50,000 respondents. Unfortunately, there are measurement issues in the dependent variable. To reduce the time required to fill each questionnaire, respondents were asked to fill information on each item when consumption was different from zero. In principle, all missing values should be zero values. However, in practice, we do not know if alcohol consumption is zero or was simply not reported.[§§§§] Moreover, non-zero consumption values are measured with significant error as well. The surveys record information on the number of days of alcohol consumption, the average number of times on each day that acohol consumption took place, the number of portions and the size of the portions (from very small to very large).[*****] Weekly intakes can only be obtained by multiplying the responses of these questions, leading to unreliable figures when large values are multiplied together.[†††††]

Therefore, we use right-censored linear regressions to deal with the problem of unreasonably high values for the number of weekly portions. We run three model with upper-limit censoring and use three different thresholds at 10, 15 and 20 standardized portions per week. In these regressions, we use municipality fixed effects, date fixed effects, and age by gender fixed effects, as well as the survey weights. We cluster standard errors at the level of municipalities. The municipality, time and gender by age fixed effects partially control for potential under-reporting biases that might correlate with the weather. The independent variables are the average temperature and the average precipitation for past seven days including the day of the interview. The dependent variable is the alcohol intake over the past 7 days, calculated by multiplying the number of days of consumption with the number of drinking occasions per day and the average portion.

[§§§§] We have non-missing data for 13.2, 17.6 and 20.2 percent of the weighted responses for alcohol consumption in the 2006, 2012 and 2018 surveys respectively. Evidence from another source suggests that a bit more than 20 percent of Mexicans declare drinking alcohol at least once a week (OECD, 2021). This suggests stronger issues of under-reporting in 2006 and 2012.

[*****] We assume that a very small portion, a small portion, a large portion and a very large portion are respectively equal to 0.25, 0.5, 1.5 and 2 times a standardised or medium portion. These standardised portions are loosely defined as 240ml of either beer, wine, pulque or Cuba libre or a smaller quantity of a stronger alcohol. Note that the alcohol content of wine is 2-3 times higher than alcohol, so standardized portions can have different levels of alcohol content.

[†††††] In the 2006 survey, we find that non-zero values ranged from 1-336 portions of 240ml of “either beer, wine, pulque or Cuba libre” in the 2006 survey. 336 portions are far beyond a lethal dose.

Results are provided in **Table 7** (in columns 1-3 for different values for the maximum consumption threshold considered for right censoring). We observe positive and statistically significant correlations between temperature and alcohol consumption.[‡‡‡‡‡] Results for precipitations are inconclusive. We also provide results with the 2018 data alone (columns 4-6) because this data is plausibly of higher quality with a smaller proportion of zero values (as explained in footnote 16) and a better measure of alcohol intake.[§§§§§] We likewise find positive and statistically significant correlations in two out of the three models. The correlation with the higher upper limit (of 20 units) is positive but loses precision.

Table 7. Correlation between the weather and alcohol consumption in Mexico

Sample	2006, 2012 and 2018 surveys			2018 survey only		
Upper-limit intake (in portions)	10	15	20	10	15	20
Average temperature (°C) of past 7 days	0.0155*	0.0316**	0.0364**	0.0174**	0.0390**	0.0314
	(0.0081)	(0.0143)	(0.0170)	(0.0083)	(0.0174)	(0.0215)
Total precipitations (mm) of past 7 days	-0.0070	-0.0028	0.0040	0.0024	0.0122	0.0166
	(0.0046)	(0.0065)	(0.0078)	(0.0064)	(0.0085)	(0.0104)

Notes: Each column corresponds to a separate regression using a truncated regression with a right upper limit (at 10, 15 or 20 units). The dependent variables are the computed alcohol consumption in standardized units over the past 7 days. Regressions include municipality fixed effects and date fixed effects and age-by-gender fixed effects. Observations are weighted with the survey weights. Standard errors are in parenthesis and clustered at the municipality level. The weather data is the CPC weather data. ***p<0.01, ** p<0.05, and *p<0.1.

Because the data on alcohol consumption is mismeasured in the nutrition data, we confirm these findings with several data sources. Firstly, we use the Mexican Survey of Household Income and Expenditure (INEGI, 2012, 2014, 2016, 2018) that provides information on daily alcohol purchases by respondents on the week preceding the interview.[******] In **Appendix G**, we estimate the correlation between these alcohol purchases and temperature. We observe a statistically significant and positive correlation between alcohol purchases and temperature with distributed lag models. The positive effect comes from temperatures that occurred 1 to 3 days before the purchase. Alcohol is non-perishable and can be stored. Therefore, these results suggest that people might replenish their stocks after a hot day has happened. Using the same data, we can show that general purchases (all goods) correlate negatively with on-

[‡‡‡‡‡] The average weekly alcohol intake in the dataset is 0.87 (4.98 for drinkers) when values are top coded at 10. When we do not top code values, the average alcohol intake is 1.29 (7.36 for drinkers). Marginal effects are therefore strong, with a 2.9-4.3 percent increase in intake per °C in column 1.

[§§§§§] In the 2018 survey, respondents were asked to express their consumption in standardised portions only (so there is only one reported size of portions). Moreover, the number of days of consumption can range from 1 to 7, whereas only four ranges of options are recorded in the 2006 and 2012 surveys (1, 2-4, 5-6 or 7 days). The answers for the number of occasions per day are also bundled in the 2006 and 2012 surveys (1, 2-3, 4-5, 6).

[******] 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.

the-day temperature.[††††††] Hence, people might not buy more alcohol on hot days because they buy less on these days in general. However, we find that they buy more alcohol on the following days when they go to buy groceries.

In **Appendix G**, we also look at online searches for terms related to “alcoholic beverages” in Mexico. We find that online searches correlate positively with monthly temperature and negatively with monthly precipitations. We obtained monthly data on online searches from 2004, but data quality is higher after 2010 due to a higher use of internet in Mexico over the past decade. Results are statistically significant when using the higher quality data after 2010. Results are positive but not statistically insignificant when using all the data since 2004.

Finally, we confirm our results on alcohol consumption and temperature in Mexico with higher-quality data on alcohol consumption collected in the U.S, focusing on the Hispanic population living in the U.S. In **Table 8,** we provide the results for the correlation between the weather and alcohol consumption using the U.S. Behavioral Risk Factor Surveillance System (2011-2019).[‡‡‡‡‡‡] Results imply that an increase in the average temperature of the past 30 days by 1°C leads to about a 1-percent increase in alcohol consumption for the general U.S. population, and to an increase of around 2 percent for the Hispanic population.[§§§§§§]

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

[‡‡‡‡‡‡] We only use the data from after 2011 because the survey weights in earlier years are not comparable. We also excluded 2020 and later years due to the impact that the COVID-19 pandemic might have had on alcohol consumption.

[§§§§§§] These results are obtained from linear regressions looking at the correlation between declared alcohol consumption during the past 30 days and the corresponding temperature and total precipitations in the U.S. State of residence of respondents. Declared alcohol consumption (the dependent variable) was obtained by asking two questions to respondents, one regarding the number of days that they drank alcohol over the past 30 days, and another on the average number of drinks consumed on each day they drank alcohol. On average, respondents consumed about 13 drinks (equivalent to a 12-ounce beer) per month (11.4 drinks on average for the Hispanic population). However, about half of interviewees declared not consuming alcohol at all during the past 30 days. The regressions include State fixed effects, interview date fixed effects, and fixed effects for the respondents’ age (in 5 year age brackets) interacted with their gender. They are weighted with survey weights and standard errors are clustered at U.S. State level.

Table 8. Correlation between the weather and alcohol consumption in the U.S.

Sample	Hispanic population	All respondents
Average temperature (°C) of past 30 days	0.2602^{***}	0.1193^{***}
	(0.0840)	(0.0308)
Total precipitations (mm) of past 30 days	-0.0296	0.0010
	(0.0765)	(0.0388)

Notes: The dependent variable is declared alcohol consumption over the past 30 days. Variables are at State level. Regressions include State fixed effects and month-by-year fixed effects. Observations are weighted with the survey weights. Standard errors in parenthesis and clustered at the State level. ***p<0.01, ** p<0.05, and *p<0.1.

Overall, the above analyses suggest that there is a positive association between daily temperature and alcohol consumption.

Temperature and crime under the influence of alcohol. We use the daily charges dataset to assess if higher alcohol consumption on hotter days could partly explain higher crime rates. In **Table 9**, we show the correlation between the charge rate for all crimes and by type of crime for offenders in normal state and drunk offenders using a model similar to Eq. (1).[*******] **Table 9** reports the absolute impact of 1°C on the charge rate per million inhabitants and the relative change in the charge rate as a share of the average daily charge rate. We also report these daily charge rates for the samples used in each regression.[†††††††] In **Appendix H**, we consider non-linearities in this relationship by using temperature bins.

Table 9 shows a sharp difference in weather-induced crimes committed in normal state versus those committed by drunk offenders. For each additional Celsius degree, the charge rate from offenders in normal state increases by 1.43 percent [1.19–1.67], while it increases by 3.69 percent [2.96–4.42] for drunk offenders. The association between temperature and crime would be 20 percent weaker if the association between temperature and the charge rate was the same for drunk offenders as for offenders in normal state.[‡‡‡‡‡‡‡] Furthermore, around 29 percent of all weather-induced crimes are committed by drunk offenders.[§§§§§§§]

[*******] Our crime data reports whether offenders were in a normal state or drunk. The information is recorded by the police and will usually come from the victim or any possible witness. The data also report if offenders were likely to be under drugs. We do not report the results for drugged offenders because this status was rarely reported. Results for drugs were inefficiently estimated.

[†††††††] The correlation between precipitations and alcohol consumption is not provided for concision.

[‡‡‡‡‡‡‡] This is the ratio between the relative effect of 1°C for offenders in normal state (1.43 percent) and the effect for all offenders, as per **Table 1**, column 1 (+0.1020 increase in absolute terms, equivalent to a 1.78 percent increase). Thus, (0.0143/0.0178) -1 ≈ -0.20

[§§§§§§§] This figure is obtained by dividing the absolute effect of 1°C for drunk offenders by the effect for all offenders of **Table 1**, column 1: $0.0298/(0.1020) \approx 0.29$

Table 9. Correlation between temperature and charge rates for offenders in normal state and drunk offenders

	Offenders in normal state			Drunk offenders		
	Charge	Effect of 1°C		Charge	Effect of 1°C	
Crime category	rate	Absolute	Relative	rate	Absolute	Relative
All crimes	4.51	0.0646***	1.43%***	0.81	0.0298***	3.69%***
		(0.0054)	(0.12%)		(0.003)	(0.37%)
By gender:						
Male offenders	8.39	0.121***	1.44%***	1.66	0.0607***	3.66%***
		(0.0101)	(0.12%)		(0.006)	(0.36%)
Female offenders	1.02	0.0123***	1.21%***	0.03	0.0012***	3.66%***
		(0.0026)	(0.26%)		(0.0004)	(1.3%)
By age group:						
Offenders below 25	7.07	0.0996***	1.41%***	1.39	0.0424***	3.05%***
		(0.0117)	(0.17%)		(0.0065)	(0.47%)
Offenders aged 25-65	7.16	0.104***	1.45%***	1.24	0.0495***	3.99%***
		(0.0104)	(0.15%)		(0.0049)	(0.39%)
Offenders above 65	1.28	0.0176**	1.38%**	0.11	0.0072**	6.77%**
		(0.0073)	(0.57%)		(0.0034)	(3.17%)
By type of crime:						
Homicide	0.15	0.0037***	2.45%***	0.03	0.0012***	3.56%***
		(0.0007)	(0.44%)		(0.0003)	(0.75%)
Injury	0.64	0.0166***	2.58%***	0.17	0.0076***	4.5%***
		(0.0017)	(0.27%)		(0.0008)	(0.49%)
Sexual crime	0.2	0.0033***	1.66%***	0.03	0.0023***	6.52%***
		(0.0006)	(0.32%)		(0.0004)	(1.19%)
Family violence	0.06	0.0022***	3.44%***	0.02	0.0012***	6.76%***
		(0.0003)	(0.5%)		(0.0003)	(1.61%)
Theft	1.34	0.0131***	0.98%***	0.21	0.0052***	2.46%***
		(0.0018)	(0.13%)		(0.0009)	(0.42%)
Fraud	0.1	0.0001	0.05%	0.001	-0.0001	-6.22%
		(0.0004)	(0.43%)		(0.0001)	(5.85%)
Property damage	0.34	0.0064***	1.87%***	0.1	0.004***	3.95%***
		(0.001)	(0.3%)		(0.0006)	(0.64%)
Kidnapping	0.06	0.001**	1.75%**	0.003	0.0001	3.21%
		(0.0005)	(0.89%)		(0.0001)	(3.06%)
Weapon-related crime	0.39	0.0051***	1.31%***	0.06	0.0024***	4.23%***
		(0.0019)	(0.49%)		(0.0004)	(0.77%)
Drug-related crime	0.37	0.0002	0.07%	0.01	0.0005***	4.92%***
		(0.0013)	(0.35%)		(0.0002)	(1.8%)
Concerted crime	0.07	0.0008	1.05%	0.01	0.0001	2.19%
		(0.0008)	(1.13%)		(0.0002)	(2.83%)
All other crimes	0.78	0.0122***	1.57%***	0.17	0.0054***	3.23%***
		(0.0022)	(0.28%)		(0.0007)	(0.42%)

Notes: 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.

Table 9 also shows that most crime categories display stronger increases in the charge rate of crimes committed by drunk offenders compared to those committed in normal state. Particularly, the relative effect for sexual crimes is four times larger for drunk offenders than for offenders in normal state. As a result, nearly 40 percent of all temperature-induced sexual crimes are committed by drunk offenders.[********] Likewise, the effect of temperature on family violence and property damage is nearly twice as high for offenders in drunk state compared to offenders in normal state.

These results do not necessarily imply that there is more crime because people consume more alcohol. A first limitation is that drunk offenders could have committed the crimes anyway without consuming alcohol. The increase in the charge rate could be *concomitant* to alcohol consumption, not *caused* by alcohol consumption. Nonetheless, because alcohol consumption is well known to have an impact on criminal incidence, aggressiveness, and disinhibition (Heinz et al. 2011, Carpenter and Dobkin 2011, Kypri et al. 2014, Biderman, De Mello and Schneider 2010), we can plausibly presume that at least some of the crimes committed under the influence of alcohol are due to the use of alcohol. According to the 2008 National Addictions Survey (SSA 2009), 18.2 percent of Mexicans between 12 and 65 consume alcohol up to the point of being drunk at least once a month. In the same survey, 5.7 percent of the Mexicans who consumed alcohol reported having engaged in a fight because of alcohol use at least once in their lives (1.9 percent in the past 12 months). Around 3.7 percent reported having had problems with police because of their alcohol consumption at least once in their lives (1.4 percent in the past 12 months).[††††††††]

The role played by alcohol misuse in criminality in Mexico is also highlighted in the victimization survey data. About 65 percent of respondents in the victimization surveys declare that they have observed street drinking in their neighborhood, and 19 percent believe that alcohol is sold illegally (e.g., without due license) in their neighborhoods. Street drinking and illegal selling also correlate with the presence of violent groups in the streets. For instance, 41 percent of the respondents of the SVPPS survey that report street drinking in their neighborhood also report the presence of violence groups in the streets. In comparison, 16 percent of respondents report the presence of violence groups among those that do not report street drinking.

Another consideration for the interpretation of **Table 9** is that criminals could be more vulnerable to the effects of alcohol on warmer days even if they consumed the same amount

[********] A linear model for sexual crimes committed by all offenders lead to an increase by 0.00609 points in the charge rate for any additional Celsius degree. The increase from drunk offenders is 0.0023 and corresponds to 37.8 percent of the overall increase for all types of offenders.

[††††††††] Alcohol consumption also exposed people to crime: 2.1% Mexicans consuming alcohol also reported being the victim of a crime while under the influence of alcohol (0.8% in the last 12 months). The crimes reported by the victims in the survey were essentially assaults, fights and injuries (40.6%), and thefts (42.5%). The survey also records a small proportion of sex crimes (3.4%).

of alcohol on cold and warm days. For example, the effects of alcohol could be stronger when people are dehydrated. In **Appendix H**, we restrict the sample to days with average temperatures between 18°C and 23°C. Focusing on temperatures within the comfort zone of the human body allows us to eliminate any interaction between alcohol consumption and thermoregulation as well as reduce risks of sample selection. Point estimates suggest that offenses committed under the influence of alcohol are temperature-sensitive within the comfort zone of the human body. These estimates are larger for drunk offenders than for offenders in normal state, although not statistically different, probably because of the reduction in sample size. This suggests that the effect of temperature on crime comes from higher alcohol consumption rather than a stronger response to alcohol consumption on hot days. However, it is possible that we register both effects at the same time: a direct effect of temperature on alcohol consumption and therefore crime; and a stronger response to alcohol at higher temperatures.[‡‡‡‡‡‡‡‡]

In **Appendix H**, we also estimate the correlation between weather and the probability that an incident reported in the victimization survey data was perpetrated by an individual under the influence of alcohol. We do not observe a statistically significant difference between the proportion of offenders under the influence of alcohol during the day. However, we find a statistically significant and positive association between temperature and the proportion of criminals under the influence of alcohol at night (midnight to 6am). This is consistent with the notion that victims and offenders might drink more on warm days because they go out more at night, and that this could explain a surge in night-time crime with warmer temperature.

II.D. Temperature and crime on weekends

Since changes in time use seem to be one of the mechanisms behind the correlation between temperature and crime, we would expect the impact of temperature and crime to be larger when people can easily adapt their schedules. We test this hypothesis in **Table 10** by comparing the association between criminal activities and temperature on weekdays versus

[‡‡‡‡‡‡‡‡] In that regard, the results by age group in **Table 9** suggest that offenders over 65, which are likely to be the most vulnerable to heat, are also those that are most responsive to a change in temperature to commit crimes under the influence of alcohol. When restricting the sample to days with average temperatures between 18°C and 23°C, results for people over 65 committing offenses under the influence of alcohol are negative and not different from zero. This indicates that people over 65 commit crimes under the influence of alcohol for temperatures outside the comfort zone of the human body. Nevertheless, results for the younger populations suggest a direct impact of alcohol consumption rather than a heightened effect of alcohol on warm days. This is because more than 40 percent of temperature-induced crimes committed under the influence of alcohol are committed by people under 25, a population with much better thermoregulation and therefore much less likely to be affected by the effect that temperature might have on sensitiveness to alcohol. Furthermore, in the victimization survey data, we found a correlation between temperature and alcohol consumption at night, when temperatures are cooler.

weekends. The main idea is that people have more flexibility in the use of their time during weekends compared to weekdays.

We find that on weekdays, a 1°C increase leads to a 1.57 percent [1.31–1.83] increase in the charge rate. On weekends, the same temperature increase is associated with a 2.23 percent [1.75–2.72] increase in the charge rate. The charge rate is therefore 40 percent more sensitive to temperatures on weekends. This difference is statistically significant at 5 percent. Results are similar for men and women. The difference between weekdays and weekends is sharper for people below 65 than for people over 65 (it is not statistically different for people above 65). This is a reasonable outcome considering that people over 65 are less likely to work and therefore less constrained on weekdays compared to younger age groups.[§§§§§§§§]

We compute that there are 12 percent more temperature-induced crimes because crimes are more sensitive to temperature on weekends compared to weekdays.[*********] We also calculate that 28 percent of the association between temperature and the charge rate can be explained from the combined differences in the temperature-induced crimes committed under the influence of alcohol and those committed on weekends instead of weekdays.[†††††††††]

[§§§§§§§§] Point estimates also suggest that the difference between weekends and weekdays affects crimes committed under the influence of alcohol as well as crimes committed by offenders in normal state. Differences between crime types are not statistically significant, except for injuries, which appear to be more weather-sensitive on weekends compared to weekdays.

[*********] This figure is obtained by comparing the effect of weekends and weekdays on the weekly crime rate: $(2*2.23/1.57*0.0877+5*0.0877)/(7*0.0877)=1.12$

[†††††††††] This is obtained by comparing the relative impact of temperatures on crime rates for offenders in normal state and on weekdays (+1.28 percent per additional degree Celsius) with the average relative impact of temperature on the charge rate of **Table 1**, column 1 (+1.78 percent per additional degree Celsius). Thus, (0.0128/0.0178) -1 ≈ -0.28

Table 10. Effect of temperature on charge rates on weekdays versus weekends

	Weekdays			Weekends		
	Charge	Effect of 1°C		Charge	Effect of 1°C	
Crime category	rate	Absolute	Relative	rate	Absolute	Relative
All crimes	5.60	0.0878***	1.57%***	6.09	0.136***	2.23%***
		(0.0075)	(0.13%)		(0.0151)	(0.25%)
By gender:						
Male offenders	10.50	0.168***	1.6%***	11.70	0.259***	2.21%***
		(0.0142)	(0.14%)		(0.0283)	(0.24%)
Female offenders	1.16	0.0138***	1.19%***	1.01	0.0218***	2.16%***
		(0.0033)	(0.28%)		(0.0059)	(0.59%)
By offenders age group:						
< 25	8.70	0.128***	1.47%***	10.60	0.223***	2.1%***
		(0.0149)	(0.17%)		(0.0333)	(0.31%)
25-65	8.92	0.143***	1.6%***	9.23	0.208***	2.25%***
		(0.0146)	(0.16%)		(0.0247)	(0.27%)
65+	1.52	0.0312***	2.05%***	1.32	0.0336**	2.55%**
		(0.0108)	(0.71%)		(0.016)	(1.21%)
Drunk offenders:						
All crimes	0.65	0.023***	3.53%***	1.20	0.0505***	4.21%***
		(0.0028)	(0.42%)		(0.0057)	(0.47%)
Offenders in normal state:						
All crimes	4.53	0.058***	1.28%***	4.44	0.078***	1.76%***
		(0.0069)	(0.15%)		(0.0125)	(0.28%)
Homicide	0.14	0.0036***	2.65%***	0.19	0.0038***	2.02%***
		(0.0007)	(0.55%)		(0.0013)	(0.72%)
Injury	0.57	0.0119***	2.08%***	0.82	0.0322***	3.92%***
		(0.0016)	(0.27%)		(0.0041)	(0.5%)
Sexual crime	0.20	0.0037***	1.84%***	0.19	0.0017	0.87%
		(0.0008)	(0.39%)		(0.0017)	(0.87%)
Family violence	0.06	0.0022***	3.55%***	0.06	0.0021***	3.41%***
		(0.0004)	(0.59%)		(0.0007)	(1.11%)
Theft	1.37	0.013***	0.95%***	1.26	0.0114***	0.9%***
		(0.0023)	(0.17%)		(0.0041)	(0.32%)
Fraud	0.12	-0.00001	-0.01%	0.07	0.00006	0.09%
		(0.0005)	(0.48%)		(0.0007)	(1.07%)
Property damage	0.32	0.0051***	1.57%***	0.39	0.0075***	1.93%***
		(0.0012)	(0.38%)		(0.0021)	(0.53%)
Kidnapping	0.06	0.0009	1.41%	0.04	0.0017*	4.05%*
		(0.0006)	(1.03%)		(0.0009)	(2.14%)
Weapon-related crime	0.39	0.005**	1.29%**	0.39	0.0032	0.82%
		(0.0021)	(0.54%)		(0.0033)	(0.84%)
Drug-related crime	0.40	-0.0002	-0.06%	0.31	-0.0024	-0.79%
		(0.0015)	(0.36%)		(0.0035)	(1.12%)
Concerted crime	0.08	0.0009	1.14%	0.06	0.0004	0.72%
		(0.001)	(1.29%)		(0.0014)	(2.23%)
All other crimes	0.83	0.012***	1.45%***	0.66	0.0164***	2.49%***
		(0.0027)	(0.32%)		(0.0041)	(0.62%)

Notes: Columns 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. They are weighted by the population in each municipality. 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. Standard errors are in parenthesis and clustered at the municipality level. ***p<0.01, ** p<0.05, and *p<0.1.

In **Appendix I**, we perform a few robustness checks to better understand the effect of weekends on crime. We find no evidence that the effect of weekends stems from changes in deterrence. We also 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 very similar but less precise since we rely on a smaller sample. Finally, we would expect the same type of effects that weekends have during holiday periods. 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 Day. Results suggest that the effect of temperature on crime may be nearly twice larger in the Christmas holiday period. However, effects between periods are not statistically different due to the smaller sample size.

III. Conclusion

We provide a thorough analysis of the correlation between temperature and crime using data for Mexico. We combine different sources of information that include reported as well as unreported crime, high-frequency data on the nature and circumstances of crime, complementary data sources on time use and alcohol consumption, and daily weather information.

Our results suggest that changes in time use and alcohol consumption might play an important role behind the short-term correlation between weather and crime. We confirm the results by Graff Zivin and Neidell (2014) that the weather influences time use. We observe an increase in the time spent away from home and alcohol consumption. Moreover, we find matching evidence that, at higher temperatures, a higher proportion of crimes happen away from home and are committed by criminals under the influence of alcohol. The association between temperature and crime is substantially higher on weekends, when people have more flexibility on their time use and can adapt their schedules more easily according to the weather. In the charges data, alcohol consumption and the effect of weekends alone can explain 28 percent of weather-induced crimes.

These results contribute to the literature and policy debate on crime policy in three ways. Firstly, we provide evidence on short-term, non-economic drivers of crime which have not been fully explored in the literature. Yet, they seem to have a sizeable influence on the decision to commit crimes. Time use and substance abuse have been repeatedly observed among offenders (e.g. Fergusson et al. 2002; Wasserman 2003; Osgood and Anderson 2004; Barnes et al. 2007). Jacob and Lefgren (2003) have also found evidence that the types of crimes committed by juveniles significantly differ on days when school is in session. Our results on the drivers of weather-induced crime are relevant to many types of crime, especially violent and sexual crimes, and they apply beyond the context of juvenile crime. With high-frequency data, we show that daily shifts in time use and alcohol consumption can potentially translate into changes in crime levels.

Secondly, there is an open debate on how to reduce crime in Latin America. In 2006 in Mexico, the government engaged in one of the most drastic wars against crime. This proved to be costly and ineffective, leading to a large surge in violent murders (Dobkin and Nicosia 2009; Escalante 2011; Quah et al. 2014; Dell 2015) that almost eliminated all the gains in life expectancy among Mexican men (Aburto and Beltran-Sanchez, 2019). Our results suggest that social policies may have been overlooked to the benefit of controversial police-fighting policies. More research is therefore needed to assess the effectiveness of policies that would reduce victimization risks, discourage alcohol consumption, and participation in antisocial activities.

Finally, scientists predict that the number of hot days will increase with climate change. Thus, the impact of the observed association between daily temperature and crime rates could worsen. Our research suggests that reducing the effect that warmer days may have on victimization risks and alcohol consumption could protect populations from one of the effects of climate change.

References

Aburto, José Manuel, and Hiram Beltrán-Sánchez. "Upsurge of Homicides and Its Impact on Life Expectancy and Life Span Inequality in Mexico, 2005–2015." *American journal of public health,* 109 (2019), 483-489.

Akers, Ronald, *Social learning and social structure: A general theory of crime and deviance* ((Routledge, 2017.

Almås, Ingvild, et al. *Destructive behavior, judgment, and economic decision-making under thermal stress*. No. w25785. National Bureau of Economic Research, 2019.

Anderson, Craig A. "Heat and violence," *Current Directions in Psychological Science,* 10 (2001), 33-38.

Anderson, Craig A., “Temperature and aggression: effects on quarterly, yearly, and city rates of violent and nonviolent crime,” *Journal of Personality and social Psychology*, 52 (1987), 1161-1173.

Anderson, Craig A., Brad J. Bushman, Ralph W. Groom, “Hot years and serious and deadly assault: empirical tests of the heat hypothesis,” *Journal of Personality and Social Psychology*, 73 (1997), 1213-1223.

Anderson, Craig A., Kathryn B. Anderson, Nancy Dorr, Kristina M. DeNeve, and Mindy Flanagan, “Temperature and aggression,” *Advances in Experimental Social Psychology*, 32 (2000), 63-133.

Anderson, Craig A., Kathryn B. Anderson, William E. Deuser, “Examining an affective aggression framework weapon and temperature effects on aggressive thoughts, affect, and attitudes,” *Personality and Social Psychology Bulletin*, 22 (1996), 366-376.

Anderson, D. Mark, Benjamin Crost, and Daniel I. Rees. "Wet laws, drinking establishments and violent crime." *The Economic Journal* 128.611 (2018): 1333-1366.

Andrews, Donald Arthur, James Bonta, *The Psychology of Criminal Conduct* (Routledge, 2014).

Auliciems, A., L. DiBartolo, “Domestic violence in a subtropical environment: Police calls and weather in Brisbane,” *International Journal of Biometeorology*, 39 (1995), 34-39.

Barnes, Grace M., Joseph H. Hoffman, John W. Welte, Michael P. Farrell, Barbara A. Dintcheff, “Adolescents’ time use: Effects on substance use, delinquency and sexual activity,” *Journal of Youth and Adolescence*, 36 (2007), 697-710.

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

Baysan, Ceren, et al. "Non-economic factors in violence: Evidence from organized crime, suicides and climate in Mexico." *Journal of Economic Behavior & Organization* 168 (2019): 434-452.

Becker, Gary S., “Crime and Punishment: An Economic Approach;” in *The Economic Dimensions of Crime*, (London, U.K.: Palgrave MacMillan , 1968) 13-68.

Bell, Paul A., “Effects of heat, noise, and provocation on retaliatory evaluative behavior,” *The Journal of Social Psychology*, 110 (1980), 97-100.

Biderman, Ciro, João MP De Mello, and Alexandre Schneider. "Dry laws and homicides: evidence from the São Paulo metropolitan area."*The economic journal* 120.543 (2010): 157-182.

Blakeslee, David S., Ram Fishman, “Weather Shocks, Agriculture, and Crime Evidence from India,” *Journal of Human Resources*, 53 (2018), 750-782.

Blakeslee, David, Chaurey, R., Fishman, R., Malghan, D., and Malik, S. "In the heat of the moment: Economic and non-economic drivers of the weather-crime relationship." *Journal of Economic Behavior & Organization*, 192 (2021), 832-856.

Burke, Marshall, Solomon M. Hsiang, and Edward Miguel, “Climate and conflict,” *Annual Review of Economics*, 7 (2015a), 577-617.

Burke, Marshall, Solomon M. Hsiang, Edward Miguel. “Global non-linear effect of temperature on economic production,” *Nature*, 527 (2015b), 235-239.

Burton, Alexander L., et al. "Belief in redeemability and punitive public opinion:“Once a criminal, always a criminal” revisited." Criminal Justice and Behavior 47.6 (2020): 712-732.

Carpenter, C., & Dobkin, C. "The minimum legal drinking age and public health." *Journal of Economic Perspectives* 25.2 (2011): 133-56.

CDC (Center for Disease Control and Prevention) (2011-2019). U.S. Behavioral Rick Factor Surveillance System. Data available here: https://www.cdc.gov/brfss/annual_data/annual_data.htm (last consulted 19th September 2022).

Chalfin, Aaron, Benjamin Hansen, and Rachel Ryley. "The minimum legal drinking age and crime victimization." *Journal of Human Resources* (2022): 0720-11070R2.

Chalfin, Aaron, Justin McCrary, “Criminal deterrence: A review of the literature,” *Journal of Economic Literature*, 55.1 (2017), 5-48.

Climate Predictions Center (CPC) (2017-2021) CPC Global Daily Temperature and Global Unified Gauge-Based Analysis of Daily Precipitation. Data provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their Web site at: https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html and https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html (downloaded on 19th, November, 2021).

Cohen, François and Antoine Dechezleprêtre, “Mortality inequality, temperature and public health provision: evidence from Mexico,” *American Economic Journal: Economic Policy*, 14, (2022), 161-192.

Cohen, Lawrence E., and Marcus Felson, “Social change and crime rate trends: A routine activity approach,” *American Sociological Review*, 44 (1979), 588-608.

Coordinación General del Servicio Meteorológico Nacional de la Comisión Nacional del Agua (CONAGUA). 1996-2020. Base de datos climatológica nacional de Mexico: datos diarios. Data accessed after requesting it from the CONAGUA (ventanillaunica.smn@conagua.gob.mx) and downloaded on February 19th, 2021.

Davis, Lucas W., Paul J. Gertler. "Contribution of air conditioning adoption to future energy use under global warming." *Proceedings of the National Academy of Sciences*112.19 (2015): 5962-5967.

Dell, Melissa, “Insurgency and long-run development: Lessons from the Mexican Revolution,” Unpublished Manuscript, 2012.

Dell, Melissa, “Trafficking networks and the Mexican drug war,” *American Economic Review*, 105 (2015), 1738-1779.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, “What do we learn from the weather? The new climate-economy literature,” *Journal of Economic Literature*, 52 (2014), 740-798.

Deschenes, Olivier, Michael Greenstone, “Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US,” *American Economic Journal: Applied Economics*, 3 (2011), 152-185.

Di Tella, Rafael, Ernesto Schargrodsky, "Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack," *American Economic Review* 94.1 (2004), 115-133.

Dobkin, Carlos, Nancy Nicosia, “The war on drugs: methamphetamine, public health, and crime,” *American Economic Review*, 99 (2009), 324-349.

Draca, Mirko, Stephen Machin, Robert Witt, "Panic on the streets of London: Police, crime, and the July 2005 terror attacks," *American Economic Review*, 101 (2011), 2157-2181.

Ehrlich, Isaac, "Crime, punishment, and the market for offenses," *Journal of Economic Perspectives*, 10.1 (1996), 43-67.

Escalante Gonzalbo, Fernando, "Homicidios 2008-2009. La muerte tiene permiso," *Nexos*, 2011.

Fergusson, David M., Nicola R. Swain-Campbell, L. John Horwood, "Deviant peer affiliations, crime and substance use: A fixed effects regression analysis," *Journal of Abnormal Child Psychology*, 30 (2002), 419-430.

Field, Simon, "The effect of temperature on crime," *The British Journal of Criminology*, 32 (1992), 340-351.

Fiscalía General de Justicia (2021) Carpetas de investigación FGJ de la Ciudad de México. Data downloaded on November 22md, 2021 from: https://datos.cdmx.gob.mx/dataset/carpetas-de-investigacion-fgj-de-la-ciudad-de-mexico

Garg, Teevrat, Gordon McCord, Aleister Montfort, "Can Social Protection Reduce Environmental Damages?". (April 29, 2020). Available at SSRN: https://ssrn.com/abstract=3465356 or http://dx.doi.org/10.2139/ssrn.3465356

Garg, Teevrat, Matthew Gibson, and Fanglin Sun. "Extreme temperatures and time use in china." *Journal of Economic Behavior & Organization* 180 (2020): 309-324.

Google LLC (2021). "Google COVID-19 Community Mobility Reports". https://www.google.com/covid19/mobility/ (Accessed: 19/11/2021).

Google LLC (2004-2019). Google trends data: online search interest for the topic "alcoholic beverage" in each of the 32 Mexican States. Available here: https://trends.google.com/trends/explore?geo=MX-MEX&q=%2Fm%2F012mj (last consulted 19th September 2022) (choose each State in the drop-down list).

Graff Zivin, Joshua, and Matthew Neidell. "Temperature and the allocation of time: Implications for climate change." *Journal of Labor Economics* 32.1 (2014): 1-26.

Graff Zivin, Joshua, Solomon M. Hsiang, Matthew Neidell, "Temperature and human capital in the short and long run," *Journal of the Association of Environmental and Resource Economists*, 5 (2018), 77-105.

Heckman, James J. "The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models." Annals of economic and social measurement, volume 5, number 4. NBER, 1976. 475-492.

Heilmann, Kilian, Matthew E. Kahn, and Cheng Keat Tang. "The urban crime and heat gradient in high and low poverty areas." *Journal of Public Economics* 197 (2021): 104408.

Heinz, A. B., Meyer-Lindenberg, A., Sterzer, P., & Heinz, A. "Cognitive and neurobiological mechanisms of alcohol-related aggression." *Nature Reviews Neuroscience* 12.7 (2011): 400-413.

Heyes, Anthony, Soodeh Saberian, "Temperature and decisions: evidence from 207,000 court cases," *American Economic Journal: Applied Economics*, 11 (2019), 238-265.

Hindelang, Michael J., Michael R. Gottfredson, James Garofalo, *Victims of personal crime: An empirical foundation for a theory of personal victimization* (Cambridge, MA: Ballinger, 1978).

Hoffman, J. R., Falk, B., Radom-Isaac, S., Weinstein, Y., Magazanik, A., Wang, Y., & Yarom, Y. (1996). The effect of environmental temperature on testosterone and cortisol responses to high intensity, intermittent exercise in humans. European Journal of Applied Physiology and Occupational Physiology, 75(1), 83-87.

Hoffman, J. R., Maresh, C. M., Armstrong, L. E., Gabaree, C. L., Bergeron, M. F., Kenefick, R. W., ... & Ward, A. (1994). Effects of hydration state on plasma testosterone, cortisol and catecholamine concentrations before and during mild exercise at elevated temperature. European journal of applied physiology and occupational physiology, 69(4), 294-300.

Horrocks, James, Andrea Kutinova Menclova, "The effects of weather on crime," *New Zealand Economic Papers*, 45 (2011), 231-254.

Hsiang, Solomon M., Kyle C. Meng, Mark A. Cane, "Civil conflicts are associated with the global climate," *Nature*, 476 (2011), 438-441.

Hsiang, Solomon M., Marshall Burke, Edward Miguel, "Quantifying the influence of climate on human conflict," *Science*, 341 (2013), 1235367.

iMaresh, C. M., Whittlesey, M. J., Armstrong, L. E., Yamamoto, L. M., Judelson, D. A., Fish, K. E., ... & stracane, V. D. (2006). Effect of hydration state on testosterone and cortisol responses to training-intensity exercise in collegiate runners. International journal of sports medicine, 27(10), 765-770.

Iyer, Lakshmi, Petia B. Topalova, "Poverty and crime: evidence from rainfall and trade shocks in India," Harvard Business School BGIE Unit Working Paper 14-067, 2014.

Jacob, Brian A., and Lars Lefgren. "Are idle hands the devil's workshop? Incapacitation, concentration, and juvenile crime." American economic review 93.5 (2003): 1560-1577.

Jacob, Brian, Lars Lefgren, Enrico Moretti, "The dynamics of criminal behavior evidence from weather shocks," *Journal of Human Resources*, 42 (2007), 489-527.

Karjalainen, Sami. "Gender differences in thermal comfort and use of thermostats in everyday thermal environments." Building and environment 42.4 (2007): 1594-1603.

Karjalainen, Sami. "Thermal comfort and gender: a literature review." Indoor air 22.2 (2012): 96-109.

Kenrick, Douglas T., Steven W. MacFarlane, "Ambient temperature and horn honking: A field study of the heat/aggression relationship," *Environment and Behavior*, 18 (1986), 179-191.

Kypri, K., Davie, G., McElduff, P., Connor, J., & Langley, J. "Effects of lowering the minimum alcohol purchasing age on weekend assaults resulting in hospitalization in New Zealand." *American journal of public health* 104.8 (2014): 1396-1401.

Larrick, R. P., Timmerman, T. A., Carton, A. M., & Abrevaya, J. "Temper, temperature, and temptation: Heat-related retaliation in baseball." *Psychological Science* 22.4 (2011): 423-428.

Levitt, Steven D, "Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not," *Journal of Economic perspectives*, 18.1 (2004), 163-190.

Maruna, Shadd, and Anna King. "Once a criminal, always a criminal?:'Redeemability'and the psychology of punitive public attitudes." European Journal on Criminal Policy and Research 15.1-2 (2009): 7-24.

Mehlum, Halvor, Edward Miguel, Ragnar Torvik, "Poverty and crime in 19th century Germany," *Journal of Urban Economics*, 59 (2006), 370-388.

Miguel, Edward., "Poverty and witch killing," *The Review of Economic Studies*, 72 (2005), 1153-1172.

Morgan, Rachel E., Jennifer L. Truman, *Criminal Victimization, 2017*. Bureau of Justice Statistics (2018).

Mukherjee, Anita, and Nicholas J. Sanders. *The causal effect of heat on violence: Social implications of unmitigated heat among the incarcerated*. No. w28987. National Bureau of Economic Research, 2021.

National Institute of Public Health (NIPH) (2006, 2012). Mexican Surveys of Health and Nutrition. Data available here: https://ensanut.insp.mx/ (last consulted 19th September 2022).

National Institute of Statistics and Geography (INEGI) (1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012). National Surveys of Household Income and Expenditure (ENIGH). Available here: https://en.www.inegi.org.mx/programas/enigh/nc/2018/ (last consulted 19th September 2022)

National Institute of Statistics and Geography (INEGI) (2009, 2014 and 2019). Mexican Surveys on Time Use. Data available here: https://en.www.inegi.org.mx/programas/enut/2019/ (last consulted 19th September 2022)

National Institute of Statistics and Geography (INEGI) (2018) National Survey on the Consumption of Energy Sources in Private Housing Units. Available here: http://en.www.inegi.org.mx/programas/encevi/2018/ (last consulted 19th September 2022)

National Institute of Statistics and Geography (INEGI), Judicial Statistics on Penal Matters of Mexico, (Aguascalientes, Mexico, 1997-2012). Available here: http://en.www.inegi.org.mx/programas/judicialespenal/ (last consulted 19th September 2022)

National Institute of Statistics and Geography (INEGI), Mexican Survey on Victimization and Perception of Public Safety (2011-2020), (Aguascalientes, Mexico, 2016). Data available here: https://en.www.inegi.org.mx/programas/envipe/2020/ (last consulted 19th September 2022)

National Institute of Statistics and Geography (INEGI). 1995, 2000, 2005 and 2010. Censos de Población y Vivienda. Conjunto de datos: Población total (con información hasta localidad). Data available on INEGI website (www.inegi.org.mx) and last accessed on 2nd January 2021.

National Institute of Statistics and Geography (INEGI). 2021. *Catálogo Único de Claves de Áreas Geoestadísticas Estatales, Municipales y Localidades*. *Marco Geoestadístico National de México*. Fecha de corte de la información: Octubre de 2010. https://www.inegi.org.mx/app/ageeml/ (last accessed 2nd January 2021).

National Institute of Statistics and Geography (INEGI). 2014. Marco Geoestadístico 2014 Versión 6.2. Available at: https://www.inegi.org.mx/app/biblioteca/ficha.html?upc=702825004386

National Institute of Statistics and Geography (INEGI) and Mexican National Institute of Public Health (NIPH) (2018) Mexican 2018 Survey of Health and Nutrition. Data downloaded here: https://www.inegi.org.mx/programas/ensanut/2018/ (last consulted 19th September 2022)

National Institute of Statistics and Geography (INEGI) and Mexican National Institute of Public Health (NIPH) (2018b) Mexican 2018 Survey of Health and Nutrition: interview dates. Data requested to INEGI at: atencion.usuarios@inegi.org.mx (obtained on 12th September 2022).

Osgood, D. Wayne, Amy L. Anderson, “Unstructured socializing and rates of delinquency,” *Criminology*, 42 (2004), 519-550.

Park, Jisung, “Temperature, test scores, and educational attainment,” Unpublished working paper, 2016.

Pratt, Travis C., Francis T. Cullen, Kristie R. Blevins, Leah E. Daigle, Tamara D. Madensen. "The empirical status of deterrence theory: A meta-analysis." *Taking stock: The status of criminological theory* 15 (2006): 367-396.

Quah, Danny, John Collins, Laura Atuesta Becerra, Jonathan Caulkins, Joanne Csete, Ernest Drucker, Vanda Felbab-Brown et al., “Ending the drug wars: Report of the LSE Expert Group on the economics of drug policy,” (2014).

Ranson, Matthew, “Crime, weather, and climate change,” *Journal of Environmental Economics and Management*, 67 (2014), 274-302.

Reifman, Alan S., Richard P. Larrick, Steven Fein, “Temper and temperature on the diamond: The heat-aggression relationship in major league baseball,” *Personality and Social Psychology Bulletin*, 17 (1991), 580-585.

Román, M.O., Wang, Z., Sun, Q., Kalb, V., Miller, S.D., Molthan, A., Schultz, L., Bell, J., Stokes, E.C., Pandey, B. and Seto, K.C., et al. (2018). NASA's Black Marble nighttime lights product suite. Remote Sensing of Environment 210, 113-143. doi:10.1016/j.rse.2018.03.017. Downloaded from https://ladsweb.modaps.eosdis.nasa.gov/search/ (series VNP46A2, period is 2012-01-01 until 2019-12-31, and area is “Mexico”) on January 19th, 2021.

Secretaria de Salud (SSA) “National Addictions Survey 2008”, (Cuernavaca, Mexico, 2009)

U.S. Bureau of Labor Statistics (2003-2019). American Time Use Surveys – 2003-2019 microdata files. Available from: https://www.bls.gov/tus/#data (last accessed 19th September 2022) (archived and included in the 2003-2020 and 2003-2021 microdata files).

US Census Bureau (2018) Cartographic Boundary Files – Shapefile: Counties (cb_2018_us_county_20m) and States (cb_2018_us_state_20m). Downloaded on May 13th, 2022 from: https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html.

United Nations Office on Drugs and Crime (2022) Victims of intentional homicides. Data available from: https://dataunodc.un.org/dp-intentional-homicide-victims (last consulted on 16th August, 2022)

Vrij, Aldert, Jaap Van der Steen, Leendert Koppelaar, “Aggression of police officers as a function of temperature: An experiment with the fire arms training system,” *Journal of Community & Applied Social Psychology*, 4 (1994), 365-370.

Wasserman, Gail A., Kate Keenan, Richard E. Tremblay, John D. Coie, Todd I. Herrenkohl, Rolf

World Meteorological Organization. *Guide to Climatological Practices*. WMO-No. 100. (2011).

Wortley, Richard. "A classification of techniques for controlling situational precipitators of crime." Security Journal 14.4 (2001): 63-82.

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

F – Additional evidence on time use and victimization risks

G – Online searches for terms related to “alcoholic beverages”

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, 1996-2020).

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

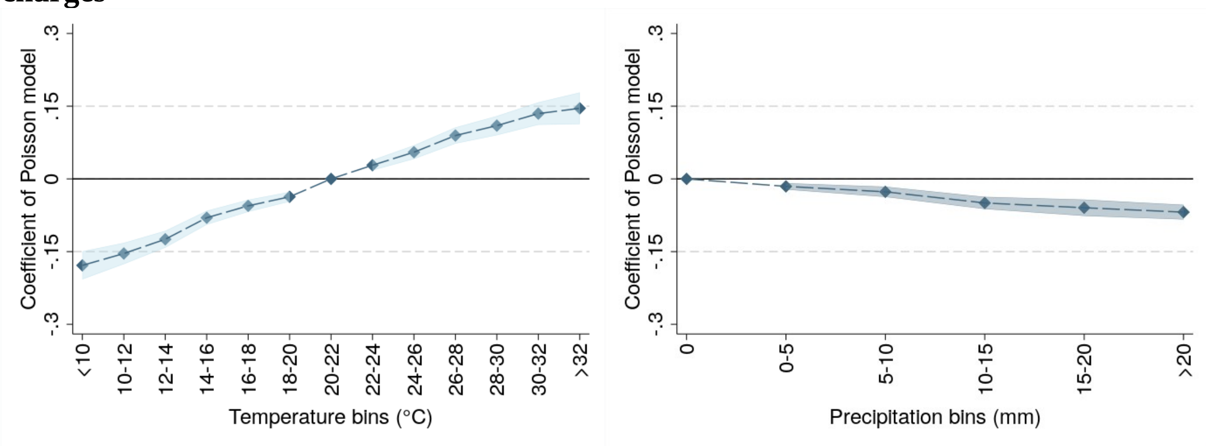
In **Appendix B.1**, instead of using linear models, we run fixed effect Poisson regressions to account for the present of zero values in the dependent variable. Results with Poisson models are very similar to those displayed on **Figure 1 and 2**. We also consider a few heterogeneous effects of temperature 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.

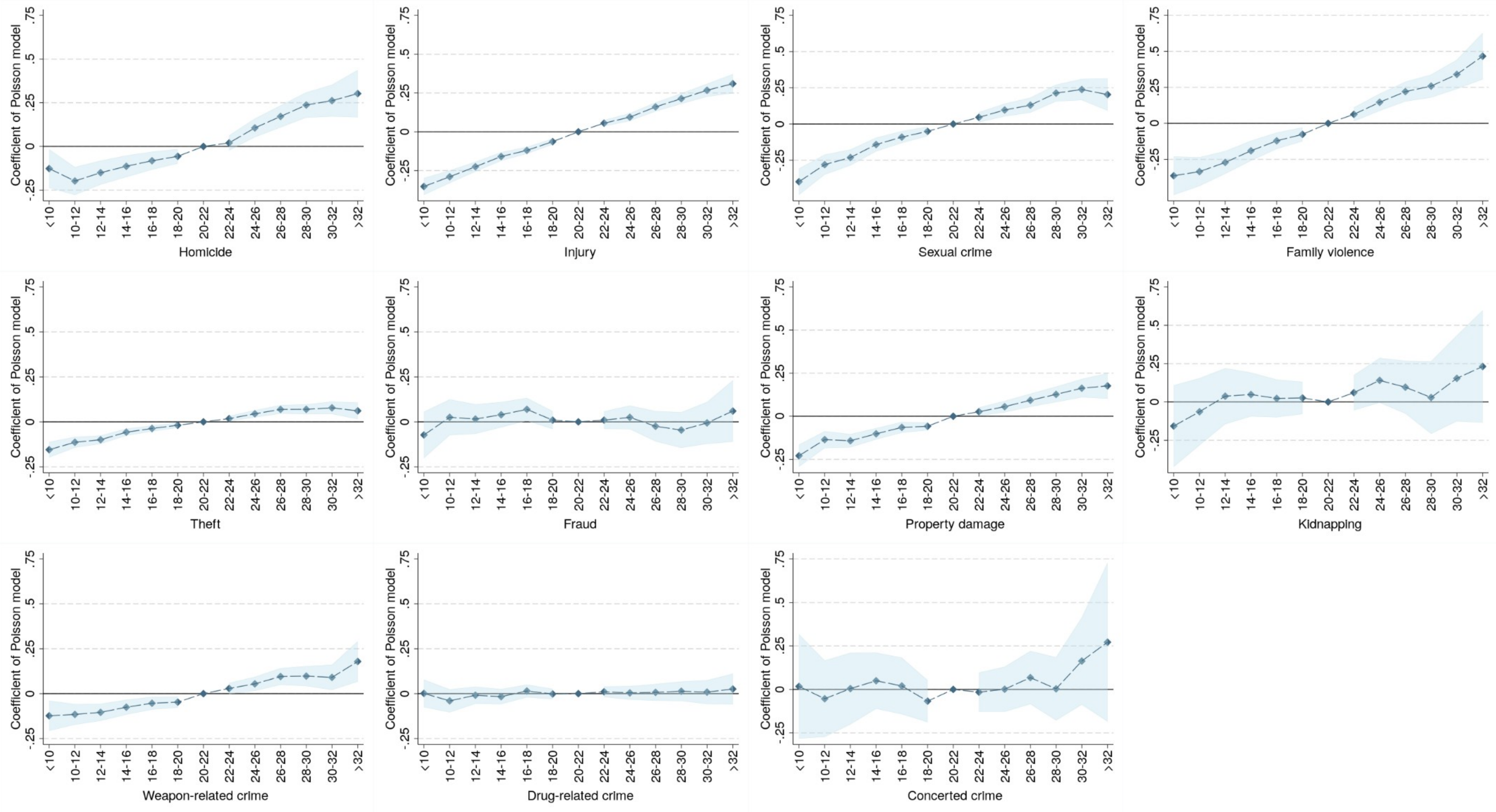
Fixed effect Poisson regressions are often used to increase the precision of estimates when the dependent variable includes many zero values. Below, we run fixed effect Poisson regressions where the dependent variables are the total number of charges in municipality *i* on day *d*, of month *m* and year *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

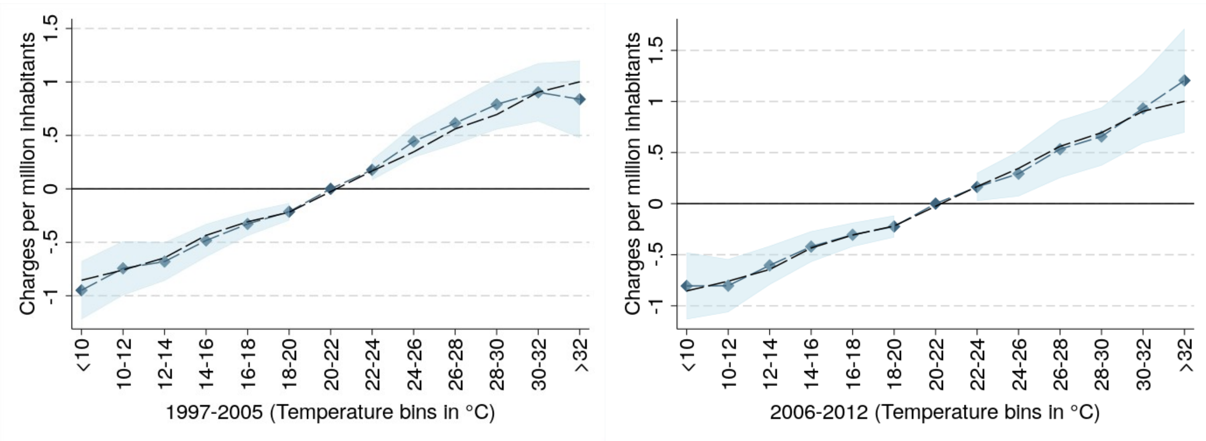


Notes: Each graph corresponds to a separate regression. The dependent variable is the daily number of charges in each category. The independent variables are all the temperature bins listed on the x-axis and five (six minus the reference) and precipitation bins (not reported in the graphs). Regressions 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.

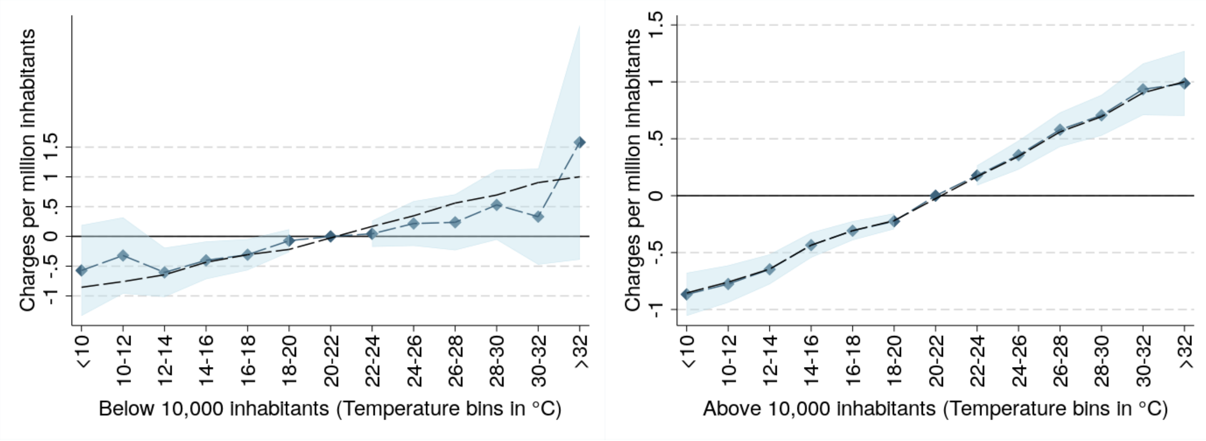
Figure B3. Correlation between temperature and the charge rate (for all types of crimes) before and after 2006



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)

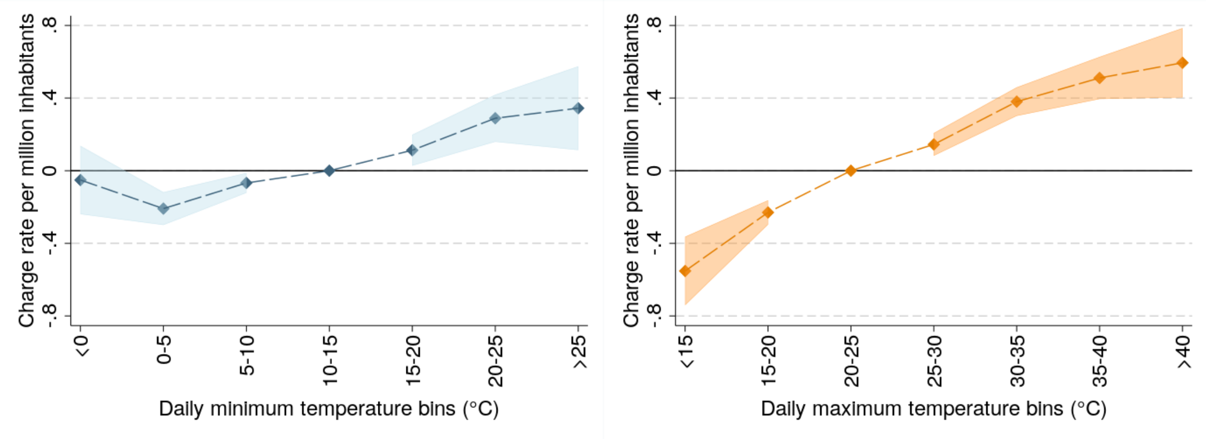
	Gender of offenders		Age of offenders		
	Male	Female	<25	25-65	>65
In charges per million people:					
All crimes	0.227***	0.0173**	0.18***	0.185***	0.0329
	(0.0298)	(0.0071)	(0.0397)	(0.0274)	(0.0249)
As a share of average rate in estimation sample:					
All crimes	2.04%***	1.49%**	1.89%***	2%***	2.17%
	(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**.[‡‡‡‡‡‡‡‡]

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.

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

[‡‡‡‡‡‡‡‡] 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.

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 .

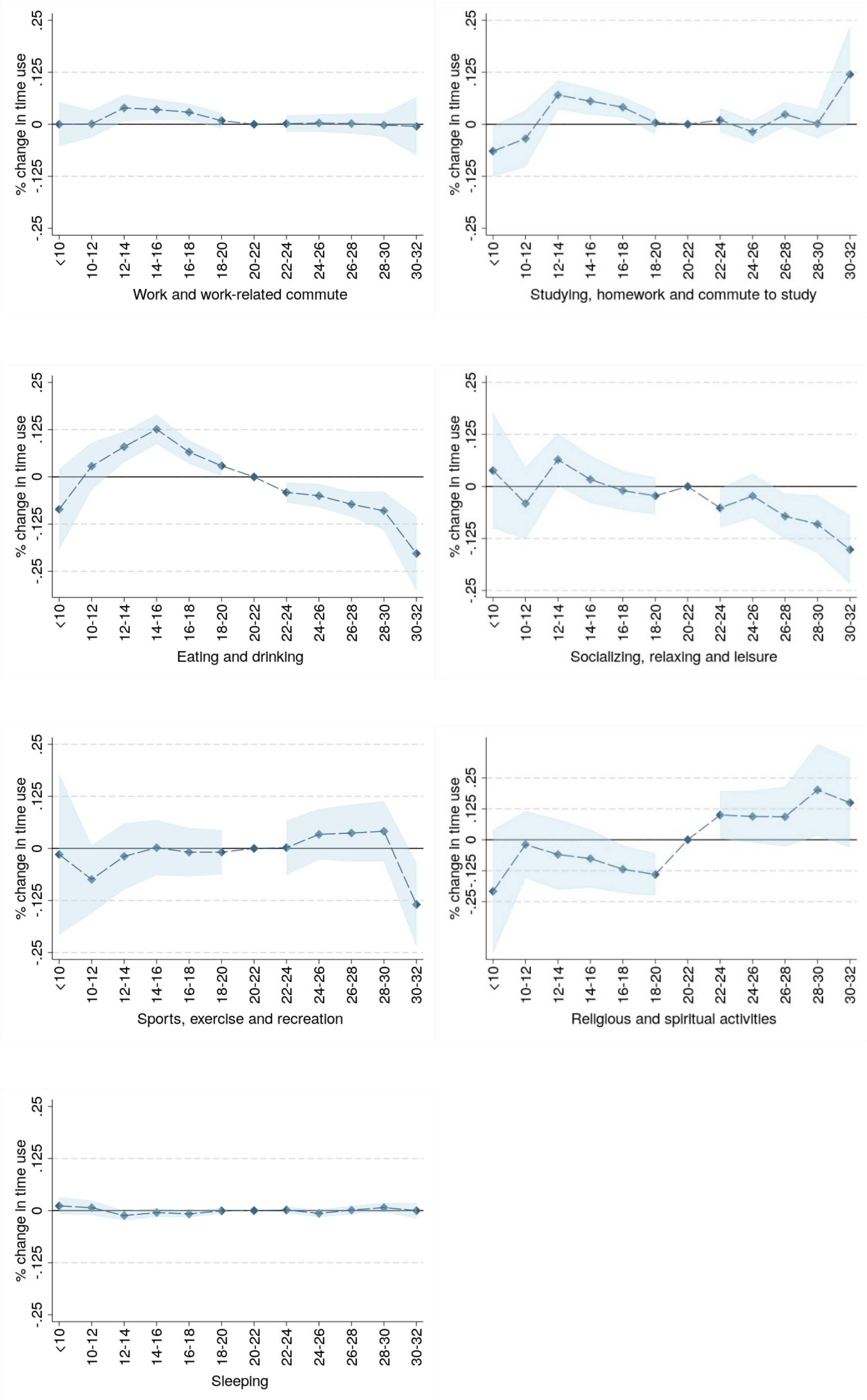
E: Complementary analyses for the impact of the weather on time use

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

$TU_{z,c,d,m,t}$ 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.[§§§§§§§§§] 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.

[§§§§§§§§§] 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

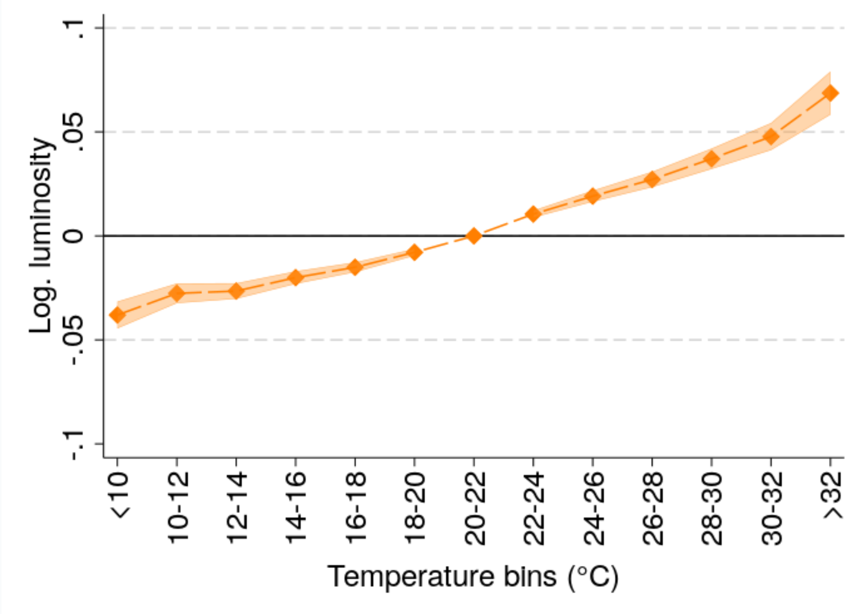
Activities	Any time of day	Morning (6am to 12pm)	Afternoon (12pm to 6pm)	Evening (6pm to 12am)	Early morning (0am to 6am)
Effect of temperature (in C):					
Time at home	-0.491*	-0.209**	-0.132	-0.135	-0.015
	(0.28)	(0.106)	(0.142)	(0.131)	(0.046)
Time outside away from home	0.125**	0.001	0.041	0.078***	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.[**********] 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

[**********] 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.[††††††††††] 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.[‡‡‡‡‡‡‡‡‡‡] 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.

[††††††††††] 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.

[‡‡‡‡‡‡‡‡‡‡] 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.

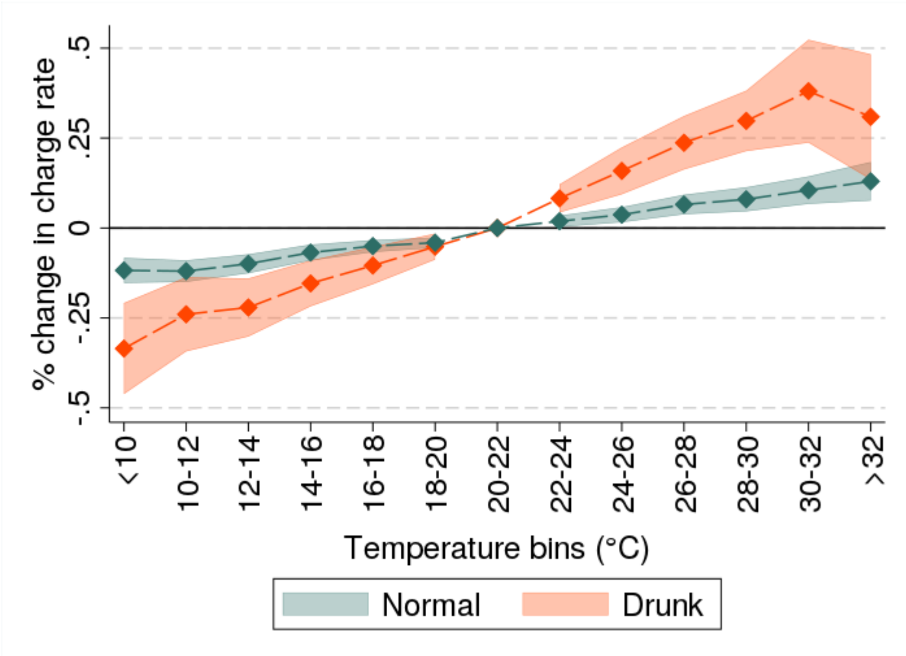
H: Additional results on the interaction between the weather, temperature, and crime

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)	-0.012 (0.03)	-0.02 (0.021)	-0.038* (0.022)	0.089** (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.