Co-benefits of Substance Abuse Regulation on Temperature and Violent Crime*

Filippo Pavanello[†] Guglielmo Zappalà[‡]

Most recent version here.

Abstract

Higher temperatures can increase substance abuse and exacerbate its physiological effects on the human body, raising the risk of violent behavior. Using administrative crime records and daily temperatures in the United States between 1991 and 2023, we show that two public policies regulating substance abuse — the expansion of substance abuse treatment facilities and the reformulation of the prescription opioid OxyContin — substantially moderate the impact of temperature on interpersonal violent crime. We monetize the policy benefits for intimate partner violence, the most widespread crime in the United States, and show that substance abuse regulations can be a cost-effective tool for climate adaptation.

JEL Classification: D91, I18, J16, K32, K42, L65, Q51, Q54

*We are grateful for constructive feedback from Anna Aizer, Max Auffhammer, Victoria Barone, Patrick Baylis, Francesco Campo, Elisabetta De Cao, Mary Evans, Libertad Gonzalez, Annalisa Loviglio, Emily Nix, Luca Perdoni, Simone Quercia, Helmut Rainer, Núria Rodríguez-Planas, Heather Royer, Vincenzo Scrutinio, and Maria Waldinger. We also thank seminar participants at the Bocconi University, LSE, University of Padova, University of Bologna, ifo Institute, RFF-CMCC European Institute on Economics and the Environment, and conference participants at AERE, CESifo / ifo Junior Workshop on Energy and Climate Economics 2025, 1st Verona Early Career Workshop for Economists, 3rd UniMI Junior Economists Meeting, 2nd Diversity and Human Capital Workshop: Well-being, and IEB Public Policy Workshop. Authors are responsible for any error in the manuscript.

†ifo Institute, LMU Munich, CESifo. Email: pavanello@ifo.de

‡Harvard University, Center for the Environment, Salata Institute for Climate and Sustainability, Cambridge, MA 02138. Email: gzappala@fas.harvard.edu

1 Introduction

Higher temperatures pose growing challenges for public health and economic well-being. In a welfare-maximizing framework, climate adaptation policies are evaluated through cost-benefit analysis that should include both direct and ancillary effects (Hahn et al., 2025; Hendren and Sprung-Keyser, 2020). Within this framework, two broad classes of adaptation policies emerge (Carleton et al., 2024): interventions explicitly designed to reduce climate damages (e.g., cooling centers, seawalls), and policies with other primary objectives but that can nevertheless generate adaptation benefits (e.g., public health facilities, education programs, social safety nets).

A large body of evidence documents that higher temperatures increase aggression and violent behavior (e.g., Anderson, 1987, 2001; Kenrick and MacFarlane, 1986; Ranson, 2014). Alcohol, opioids, and other substances impair cognitive and emotional functions, and higher temperatures can both increase their consumption (Cohen and Gonzalez, 2024) and amplify their behavioral effects through psychological and physiological channels (Hensel et al., 2021; Jhang et al., 2025), leading to more violent behavior (Luca et al., 2015). As a result, policies targeting substance abuse may generate ancillary adaptation benefits by moderating the effects of temperature on violent crime.

In this paper, we examine whether public policies that regulate access to addictive substances can mitigate one of the major social consequences of rising temperatures: violent behavior and crimes. We study two major public policies in the United States that address abuse of substances, including alcohol and opioids. First, we exploit variation in the staggered opening of substance abuse treatment facilities (SAT) across counties between 1998 and 2016. Second, we leverage a nation-wide intervention in 2010 that reformulated OxyContin, the most widely prescribed legal opioid at the time, to curb overprescription and mitigate its addictive risks. We combine the variation induced by the policy environment with daily temperature fluctuations to estimate whether and how these interventions alter the temperature-crime relationship.

We begin our analysis by documenting four motivating facts that inform our analysis. First, using FBI administrative data from 1991 to 2023, we show that a 1°C increase in daily average temperature is associated with 0.0047 additional crimes per 100,000 people per day (about 0.7% relative to the sample mean). The effect is larger for violent crimes — including intimate partner violence — than for monetary crimes (1% versus 0.5%, respectively), and is small and statistically imprecise for crimes that involve limited interactions between victims and offenders, such as fraud and gambling. Second, we show that higher temperatures increase substance consumption and its consequences. On the one hand, using individual time use data from surveys we document that higher temperatures are positively associated with alcohol consumption and heavy drinking, with effects more pronounced in counties with higher opioid use, providing suggestive evidence of "polysubstance use", i.e., a complementarity between the two substances (Esser et al., 2019, 2021). On the other hand, we show that higher temperatures exacerbate the health consequences of opioid use, increasing opioid-related emergency department visits. Third, we show that higher temperatures physiologically accentuate the behavioral effects of substance use, by increasing violent crimes involving offenders under the influence, particularly alcohol, cocaine, marijuana, and stimulants. Fourth, the temperature–violent crime gradient is steeper in counties with higher baseline opioid consumption. Altogether, these facts indicate that substance use is a major channel in the temperature-crime relationship.

Building on these empirical patterns, we design an empirical strategy to causally identify the extent to which substance abuse regulation moderates the effect of temperature on crime. Our preferred specification exploits variation in daily temperatures and crimes within jurisdiction, comparing crime outcomes on relatively hotter or colder days within the same month and year. We flexibly control for temporal unobserved heterogeneity at the day of the week, week of the year, and day of the year level. In addition, we allow the direct effects of temperatures and precipitation on crime to vary over time and across space, so as to account for other potential unobserved county-level or annual changes in weather-crime relationship even in the absence of policy changes. We also show that the two policies vary independently, and that variation in SAT facilities is unrelated to local temperatures, opioid prescriptions, and the OxyContin reformulation.

We find that a 1°C increase in daily temperatures is associated with 0.0008 fewer violent crimes per 100,000 people after the opening of an additional SAT per 100,000 people, corresponding to about 20% of the direct effect of temperature at the mean. Similarly, a 1°C increase is associated with 0.034 fewer cases per 100,000 people after the 2010 opioid reformulation, which corresponds to roughly an 11% reduction relative to the pre-reformulation average violent crime rate. Our event-study results provide support to our parallel trend assumption and show that the attenuating role of the policy persists over more than ten years.

We explore several mechanisms through which these policies may attenuate the temperature–violent crime gradient. First, we show that both policies reduce the impact of higher temperatures on substance-involved violent crimes. This mitigating effect is concentrated primarily in offenses involving alcohol. Because alcohol-related crimes constitute the majority of substance-involved violent crimes in our data, the presence of an effect for the OxyContin reformulation provides novel suggestive of cross-substance interactions between opioid and alcohol use. Second, we also show that the effectiveness of the policies depends on the scope for substitution across drugs. For SAT expansion, which targets multiple substances simultaneously, we find no evidence of substitution toward other drugs. In contrast, the mitigating effect of the OxyContin reformulation is muted in settings with greater access to substitutes. We find no attenuation of the temperature–crime relationship in states with legal medical marijuana or in counties near the Mexican border where fentanyl availability is greater (Evans et al., 2019, 2022; Sabia et al., 2024).

Third, we find suggestive evidence consistent with biophysical adaptation. Both policies are more effective in colder counties, whereas the effects are smaller and noisier in hotter counties. This may suggest greater physiological tolerance to higher temperatures in warmer climates, which weakens the interaction between higher temperatures and substance abuse in increasing crime rate, and thus reduces the effectiveness of substance abuse regulation. Fourth, we show that the moderating effect of both policies is not driven by changes in the timing of criminal activity. Exploiting intra-day temperature variation, we find that the policy is effective over all hours of the day, but more largely in the evenings and at nights. We also find a larger effect of the policy on weekends, consistent with substance consumption and temperature-related violent crime peaking when individuals can adjust their schedule more easily (Cohen and Gonzalez, 2024; Kuntsche and Labhart, 2012; Yan and Kuo, 2019).

We quantify the welfare-relevant climate adaptation benefits of substance abuse policies through reductions in intimate partner violence, one of the most prevalent and socially costly violent crimes in the U.S.[1] We estimate that, for a 1°C increase in average temperature, the SAT expansion and the opioid reformulation generate respectively annual net social benefits of approximately $13 million and $37 million (in 2023 US$) from avoided intimate partner violence. Because such adaptation benefits are excluded from standard evaluations of substance-abuse interventions, our results suggest that existing welfare analyses may substantially understate the social value of these policies in a warming climate.

Our findings contribute to a well established literature that examines the effect of temperature on violent behavior, one of the major socio-economic impacts of climate (Carleton and Hsiang, 2016). Higher temperature can increase aggressivity and induce violent behavior through physiological channels (Baylis, 2020; Behrer and Bolotnyy, 2022; Cohen and Gonzalez, 2024; Evans et al., 2025; Fetzer, 2020; Heilmann et al., 2021; Mukherjee and Sanders, 2021; Ranson, 2014). We contribute to this literature by documenting a strong positive linear relationship between daily temperature and violent crime in the United States over more than thirty years. The temperature effect is robust across crime categories involving close social interactions, including for intimate partner violence, a relationship that has never been documented before in the U.S. We also show that higher temperatures increase crimes involving substance use (e.g., alcohol, drugs), and differentially more in areas more exposed to the opioid epidemic, highlighting a central channel between temperatures and violent behavior.

Our paper contributes to the literature evaluating public policies that mitigate climate impacts on socio-economic outcomes (see Carleton et al. (2024) for a review). The vast majority of prior work exploits changes in budget constraints through cash transfers programs, humanitarian aid programs, or income shocks to study how these interventions mitigate the impact of climate shocks on education and labor market outcomes (Adhvaryu et al., 2024; Garg et al., 2020; Macours et al., 2022), on food security and health (Avdeenko and Frölich, 2025; Premand and Stoeffler, 2022), on mortality (Banerjee and Maharaj, 2020; Sarmiento et al., 2024), and on violent behavior (Baysan et al., 2019; Christian et al., 2019; Fetzer, 2020; Garg et al., 2025). Other works show that health care access and services attenuate the temperature-mortality relationship (Cohen and Dechezleprêtre, 2022; Mullins and White, 2020), and more restrictive gun laws attenuate the impact of temperatures on homicide (Colmer and Doleac,

[1] Approximately one in five reported violent crimes in our data involve intimate partner violence.

2023). Prior reviews document limited evidence of adaptation on crime, violence, conflicts, and suicide (Burke et al., 2015, 2024; Carleton and Hsiang, 2016; Carleton et al., 2024). We provide first evidence of successful examples of non-income adaptation interventions for crime and violence, and monetize the benefits of substance abuse regulation policies to the temperature-crime relationship.

Finally, our paper contributes to the literature on substance abuse regulation. Prior work shows that expanding substance abuse treatment facilities reduces substance use, substance-related mortality, and crime (Bondurant et al., 2018; Mitchell et al., 2012; Prendergast et al., 2017; Swensen, 2015). We also contribute to the growing literature on the U.S. opioid epidemic (Arteaga and Barone, 2026; Dave et al., 2025; Evans et al., 2019). Recent studies document that the reformulation of OxyContin and must-access prescription drug monitoring programs had unintended consequences, increasing child maltreatment and foster care entry (Evans et al., 2022; Gihleb et al., 2022). We document sizable positive climate adaptation spillovers of substance abuse treatment facilities and of the OxyContin reformulation. Our results highlight an important welfare-relevant externality of substance-abuse policies that is not accounted for in conventional cost–benefit analyses.

2 Data and policy background

In this section, we describe the data for our empirical analysis. We retrieve comprehensive administrative data on reported crimes at the finest temporal and geographic scale available in the U.S. (Section 2.1), and we combine them with climate data (Section 2.2). We describe and provide background information on our two main substance abuse regulation policies, respectively substance-abuse treatment facilities (Section 2.3), and the abuse-deterrent reformulation of OxyContin in 2010 (Section 2.4). We complement our analysis with a number of additional data sources at the individual-, county-, and state-level to explore mechanisms and channels of the relationship between temperatures, substance abuse, and crime. Appendix Table A1 reports summary statistics for the main variables.

2.1 Crime data

We use data from the FBI's National Incident-Based Reporting System (NIBRS) for the period between 1991 and 2023. NIBRS records all criminal incidents reported to individual law enforcement agencies (ORIs or jurisdictions) and includes detailed information on the characteristics of the victim (e.g., age, gender), the offender (e.g., gender and relationship to the victim), the crime (e.g., category of crime, substances involved), and the incident date and time.

Leveraging the reported offenses within each incident, we construct daily counts by crime category.[2] Broadly, we categorize crimes into two main categories: violent and monetary. The former category includes assault, rape, and homicide; the latter includes robbery, motor-vehicle theft, burglary, larceny, gambling, and fraud. For each crime category, we compute the daily rate of reported incidents per 100,000 people.[3]

We also exploit information on the victim–offender relationship to construct daily counts of intimate partner violence (IPV) towards females. We define IPV to include aggravated assaults, simple assaults, forced sex, and intimidation, experienced involving female victims and offenders identified as spouses, common-law spouses, boyfriends or girlfriends, homosexual partners, ex-spouses, or ex-boyfriends/girlfriends.[4]

NIBRS also reports whether the offender was under the influence of substances at the time of the offense. This information, however, is available only for alcohol and an unspecified drug category. To obtain substance-specific measures, we refine our classification of drug-involved crimes using detailed information on the types of drugs seized during the incident, including heroin, cocaine, marijuana, stimulants, and hallucinogens.[5]

[2]Unlike the traditional Uniform Crime Reports (UCR) system, which records only the most serious offense in an incident ("hierarchy rule"), NIBRS allows agencies to report up to ten types of crime per incident. We treat each incident as one crime when constructing overall crime counts. When computing crime-specific counts, we count each reported crime separately. For example, if an incident involves assault and vandalism, we count each as one additional crime in each respective category.

[3]We construct population at the jurisdiction-level from two different source: the ICPSR website at the University of Michigan, and the FBI's Crime Data Explorer (CDE). Jurisdiction-level population is not available for all the agencies. We test that our results are robust to the unrestricted sample, using the daily count of reported crimes as a dependent variable and estimating a PPML model.

[4]To our knowledge, this is the first paper to examine the effects of temperature on intimate partner violence in the U.S. Appendix B provides additional details.

[5]For example, a crime is classified as "heroin-involved" if the offender is reported as under the influence of

Agencies reporting crime data increase over time, from 609 in 1991 to 13,125 in 2023, with departments entering and exiting the sample over time (Figure A1). To attenuate concerns over the unbalancedness of our sample, we construct a panel at the jurisdiction-day level that is balanced for each year, and leverage within-month-year variation.

A common concern when using administrative crime data is that recorded offenses may reflect changes in policing or reporting rather than underlying criminal behavior, if, for example, police effectiveness, evidence collection, or reporting behavior varied with temperatures. In these cases, sample selection could be confounding the relationship between temperatures and crime. While we cannot directly rule out these mechanisms, prior work finds that they play a limited role in explaining the temperature-crime relationship (e.g., Cohen and Gonzalez, 2024; Evans et al., 2025; Heilmann et al., 2021). In our setting, our baseline specification accounts for short-run local unobserved confounders such as heat adaptive policing, local-based enforcement or temporary staffing changes, by holding characteristics for each month in a given year in a given jurisdiction fixed. We also show that our results are robust to alternative specifications that vary the spatial and temporal structure of fixed effects, thereby capturing different potential unobserved changes in evidence gathering, police effectiveness, and reporting behavior.

2.2 Weather data

We process weather data from the ERA5-Land reanalysis product (Muñoz Sabater, 2019), which provides hourly temperature and precipitation from 1950 to present at a 0.1° spatial resolution (≈ 11km). We combine weather data with 30 arc-seconds (≈ 1km) population density information (Seirup and Yetman, 2006) to compute the county-level population-weighted average daily temperature and total precipitation. In additional analysis, we also construct sub-daily temperature exposure during different times of the day.

---

drugs and heroin is seized during the incident. As with any administrative data, measurement error may arise from over- or under-reporting of specific substances, particularly in cases of polysubstance use.

2.3 Substance-abuse treatment facilities

Our first policy of interest is the opening of substance abuse treatment (SAT) facilities. These centers constitute the primary setting for the delivery of treatment and rehabilitation services for individuals with substance use disorders. Admissions are primarily for alcohol (22%), opioids (19%), and combined alcohol and secondary drug use (18%). The establishment of new clinics typically depends on (i) local assessments of unmet treatment needs or opportunities to expand available services and (ii) the ability to secure funding (SAMHSA, 2018).

We collect annual data on the number of open substance abuse treatment facilities at the county-level from the U.S. Census Bureau's County Business Patterns (CBP) for the 1998-2016 period.[6] The CBP reports the number of SAT establishments in each county, but only for counties with at least one active facility.[7] For our main analysis, we restrict the sample to counties with at least one SAT facility open at any point during the study period. We then construct the annual rate of SAT facilities per 100,000 people at the county level. In robustness checks, we consider alternative treatment definitions: (i) the count of establishments in a county, (ii) an indicator for whether a SAT facility opened in the county in the previous year, and (iii) an indicator for the first SAT facility opening in the county so as to capture the extensive margin of treatment access rather than its changes in the intensive margin. Figure A2 reports the total number of SAT establishments over time, steadily increasing over time. Figure A3 shows their distribution across the U.S., weighted by population. Between 1998 and 2016, U.S. counties have on average 6 SAT facilities per 100,000 people, with 16% of counties, especially in the Midwest and North-East, hosting more than 10 facilities per 100,000 residents.

2.4 2010 OxyContin reformulation

Our second policy of interest is the reduction in access to prescription opioids following the 2010 reformulation of OxyContin. Prescription opioid use in the U.S. expanded rapidly over the preceding decades, with the number of opioid prescriptions rising from 76 million in 1991

[6] We identify substance abuse treatment establishments in the CBP data using two NAICS codes: 621420 ("Outpatient mental health and substance abuse center") and 623220 ("Residential mental health and substance abuse facilities") (Bondurant et al., 2018; Swensen, 2015).

[7] Starting in 2017, the CBP only reports counties with three or more SAT facilities, hence we restrict our analysis to data through 2016.

to more than 250 million by 2010 (Volkow et al., 2014). OxyContin, introduced by Purdue Pharma in 1992, played a central role in this expansion. The drug contains oxycodone — a narcotic analgesic originally prescribed for moderate to severe chronic pain — but is also associated with a high risk of addiction and non-medical misuse.

To address growing concerns about misuse and diversion, Purdue Pharma developed an abuse-deterrent formulation of OxyContin designed to make the pills more difficult to crush or dissolve and take via non-oral routes. The U.S. Food and Drug Administration approved the reformulated version in April 2010, and nationwide distribution began in August 2010, when the original formulation was discontinued without advance public notice. The reformulation led to a sharp decline in OxyContin misuse (Cicero and Ellis, 2015; Sessler et al., 2014), but it also triggered substitution toward illicit opioids such as heroin and synthetic opioids, reflected in the subsequent rise in overdoses (Powell and Pacula, 2021). We exploit the 2010 nationwide reformulation of OxyContin — an unanticipated, unilateral decision by Purdue Pharma — as an exogenous policy shock to availability of prescription opioids.

To measure pre-reformulation differential exposure to prescription opioids, we use the county-level population-weighted average number of Schedule II opioid prescriptions per capita during 2006-2009, obtained from the Centers for Disease Control and Prevention (Evans et al., 2022). The CDC data cover approximately 85% of retail pharmacy providers but exclude hospital dispensing. This measure captures a broader class of prescription opioids than the OxyContin itself, but provides finer county-level geographic variation than prior studies based on state-level data (Alpert et al., 2022). Figure A4 shows the spatial distribution of population-weighted average number of opioid prescriptions per capita in the pre-reformulation period. The sample average is 0.85 opioid prescriptions per capita (Table A1 reports weighted averages), and about 30% of counties recorded more than one prescription per resident.

As an alternative source for robustness, we also use county-level data from the Drug Enforcement Administration's Automation of Reports and Consolidated Orders System (ARCOS), which records shipments of controlled substances to retail pharmacies. Using ARCOS, we compute alternative measures of opioid exposure based on the average number of Schedule II opioid pills distributed and the number of shipments per capita over 2006-2009.

2.5 Additional data

As part of our analysis, we incorporate several auxiliary data sources, summarized below.

Alcohol consumption. To examine how alcohol consumption varies as a function of temperature, we use data from the U.S. Behavioral Risk Factor Surveillance System (BRFSS), an annual health-related telephone conducted by the Center for Disease Control and Prevention. The BRFSS is one of the world's largest continuous health survey systems and provides nationally representative information on several health dimensions between 1991 and 2012.[8] The survey includes information on whether respondents consumed alcohol in the past months, and the average number of drinks consumed per drinking day. It also reports respondents' socio-economic and demographic characteristics. We construct a repeated cross-section with over four million observations, which we match to weather data using the interview date and county of residence.

Medical marijuana laws. In complementary analysis, we examine whether the effectiveness of our substance abuse policies varies with legal access to marijuana as a therapeutic substitute. We use state-level information on the timing of medical marijuana legalization from the National Conference of State Legislatures.

3 Motivating facts: Temperatures, crimes, and substance abuse

Changes in ambient temperature can affect violent behavior through multiple channels. A large literature documents direct physiological and psychological effects of temperatures on impulse controls, irritability, and aggression (Anderson, 1987, 2001; Kenrick and MacFarlane, 1986). Higher temperatures can affect both the prevalence and the consequences of substance use. Two co-existing mechanisms may be at play. First, higher temperatures may increase the likelihood of substance use through physiological stress, behavioral adjustments, or changes in time use (Cohen and Gonzalez, 2024). Higher temperatures can deteriorate mental health, increase anxiety, despair and isolation (Mullins and White, 2019), which in turn can raise the

[8] We end the sample in 2012, the last year for which county of residence is available.

propensity to consume alcohol or opioids (Gros et al., 2013; Martins et al., 2012), and induce aggression and violent behavior (Barron et al., 2024; Dave et al., 2025; Deiana and Giua, 2021; Luca et al., 2015). Second, conditional on consumption, higher temperatures may amplify the physiological consequences of substances — through mechanisms such as vasodilatation and blood pressure increase — thereby increasing violent behavior (Herrnstein and Wilson, 1985; Miczek et al., 2004; Sim, 2023). Although empirically separating these channels is challenging, both imply that policies regulating substance abuse may reduce the sensitivity of violent crime to temperatures.

Using our data, we document four motivating facts on the relationship between temperature, crime, and substance use in the United States. We focus on alcohol and opioids, the two most prevalent legal substances linked to violent behavior and often jointly consumed as complements in patterns of polysubstance use (Esser et al., 2019, 2021).

Fact 1: Temperatures increase crime. We begin by documenting the well-established relationship between temperature and crime in our data. Using data over more than thirty years across U.S. jurisdictions, we estimate the relationship between daily temperatures and different categories of crime. We exploit variation in a given jurisdiction for each month-year, while accounting for temporal fixed effects at the week-of-year, day-of-year, and day-of-week level (see Appendix C for additional details).[9]

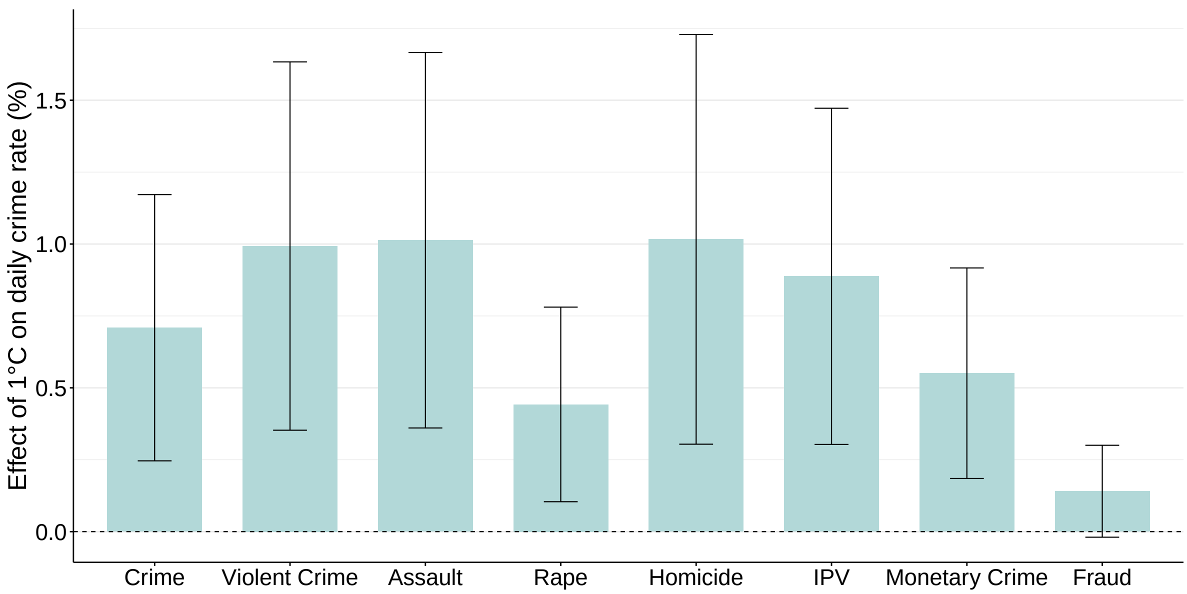
Figure 1 displays the estimated coefficients (normalized by the weighted mean outcome). A 1°C increase in daily temperature is associated with 0.0047 additional crimes per 100,000 people, corresponding to about a 0.7% increase relative to the mean. The effect is concentrated in violent crimes: a 1°C rise increases violent crimes by 1%, compared to 0.5% for monetary crimes. Disaggregated results by category of crimes show that assaults and homicides rise by 1%, and rapes by 0.6%, with similar patterns for intimate partner violence involving female victims. By contrast, monetary crimes such as fraud—where interactions with victims are limited or absent—respond weakly and imprecisely to temperature (0.1% at the mean).

Altogether, these results are consistent with prior evidence that attributes the temperature-

[9] In Appendix C, we assess alternative functional forms for temperature and precipitation and find no evidence against linearity, similar to prior work (e.g., Cohen and Gonzalez, 2024; Colmer and Doleac, 2023; Heilmann et al., 2021). We therefore adopt the linear specification as our preferred approach throughout the analysis.

crime relationship primarily to interpersonal and affective channels rather than economic motives (Cohen and Gonzalez, 2024; Colmer and Doleac, 2023; Heilmann et al., 2021; Ranson, 2014). Higher temperatures increase physiological stress, irritability, and impulsivity, increasing the likelihood of aggressive responses in social interactions, while leaving premeditated or opportunity-driven crimes largely unaffected. This evidence reinforces the interpretation that temperature primarily increase violence through behavioral mechanisms, motivating our subsequent analysis of how substance abuse regulations may modulate the temperature impacts on violent interpersonal crimes.

Figure 1: Effects of daily temperatures on daily crime rate by category in the U.S. through 1991 and 2023



Notes: The figure plots the coefficients of temperature on crime rates (per 100,000 people) normalized by weighted sample mean. The regressions control for daily total precipitation, and jurisdiction-month-year, day-of-year, week-of-year and day-of-week fixed effects. Regressions are weighted by jurisdiction-location population. Confidence intervals at 95% are reported with standard errors clustered at the county-level. Table C1 reports the unweighted coefficients.

Fact 2: Temperatures increase substance abuse. We provide two pieces of evidence consistent with substance use as a physiological mechanism linking temperatures to violent behavior. First, using individual-level data from the Behavioral Risk Factor Surveillance System (BRFSS), we document that higher temperatures raise alcohol consumption. Exploiting county-level temporal variation in average temperatures over the thirty days prior to interview date, we find that a 1°C increase in daily average temperatures increases the likelihood of heavy drinking by 0.04-0.06 percentage points, corresponding to a 0.6-0.8% increase relative to the mean (Table 1, columns 1-3).[10] We also show that the effect of temperature on heavy drinking is significantly larger in high-opioid-exposure counties (column 4). In these counties, a 1°C increase in daily average temperature raises the likelihood of heavy drinking by 0.07 percentage points (0.98% relative to the mean), while the effect is smaller and not statistically significant in less exposed counties, providing suggestive evidence in support of a positive association between alcohol consumption and prescription opioid use.

Table 1: Effect of monthly temperatures on alcohol consumption using individual-level survey data

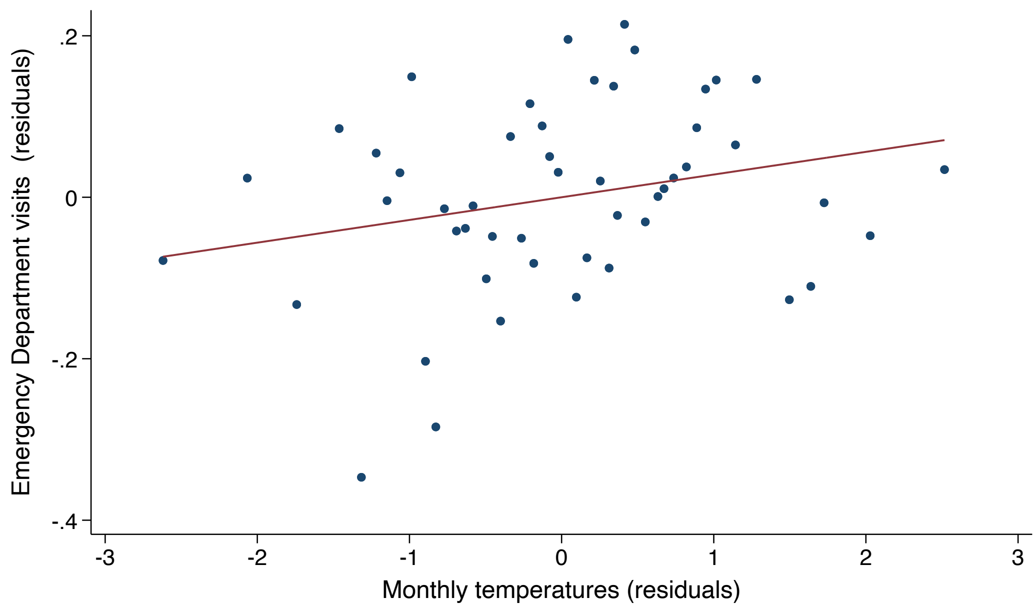
	Heavy Drinking (0/1)			
	(1)	(2)	(3)	(4)
30-day Temperature	0.000468***	0.000569***	0.000425**	0.000336
	(0.000)	(0.000)	(0.000)	(0.000)
30-day Temperature × High opioid exposure				0.000325**
				(0.000)
30-day Precipitation	0.00263	0.0131	0.0143*	-0.0178
	(0.006)	(0.008)	(0.008)	(0.0110)
Period	1991-2012	1991-2012	1991-2012	2006-2009
Observations	3,994,304	3,994,304	3,793,862	1,228,916
Mean Outcome	0.073	0.073	0.073	0.071
Individual controls			✓	✓
County FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
State-Month FE		✓	✓	✓

Notes: The dependent variable is a dummy variable indicating whether the individual was a heavy drinker in the last month. Heavy drinking indicates whether in the last month an individual has consumed more than 56 drinks if male, and 28 drinks if female. "High opioid exposure" is a dummy variable equal to one if individual lives in a county where opioid prescriptions per capita are at or above the 75th percentile. "Individual controls" include education level, employment status, age, number of family member, and race from the BRFSS. Standard errors are clustered at the county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

[10] Heavy drinking is defined as at least 28 (56) drinks in the previous month for women (men). These findings are robust to alternative measures of alcohol consumption: higher temperatures increase both the probability of any alcohol use and the number of drinks in the past month (Table D1).

Second, we examine the relationship between temperatures and opioid-related harm. Although individual-level data on opioid use are not available, using monthly state-level data we show that higher temperatures exacerbate opioid-related health consequences. Figure 2 shows a positive and statistically significant association between temperature and non-fatal opioid-related emergency department visits (p-value = 0.041), in line with prior evidence (Chang et al., 2023; Parks et al., 2023). While the data do not allow us do disentangle whether higher temperatures primarily increase opioid consumption or amplify its physiological risks, both mechanisms imply that warmer conditions can intensify opioid-related harms.

Figure 2: Temperature and non-fatal opioid-related emergency department visits



Notes: Figure shows binned scatterplots with 50 bins and a linear regression (coefficient = 0.0281, standard error = 0.0138) on the underlying data on the correlation net of state-month, state-year, month-year fixed effects between residualized monthly rate of emergency department visits for nonfatal opioid overdose and residualized monthly temperatures at the state level for the 2018-2021 period. Data on Nonfatal Opioid-related Overdose Emergency Department visits from Centers for Disease Control and Prevention (2024).

Fact 3: Temperatures increase substance-involved crime. Building on evidence that higher temperatures increase alcohol consumption and exacerbate the physiological consequences of opioid use, we examine whether these effects translate into more substance-involved violent behavior. Figure 3 displays the estimated effects of daily temperatures on violent crimes, assaults, and intimate partner violence, where the offender was reported to be under the influence of any substances, as well as alcohol, drugs, heroin, cocaine, marijuana, hallucinogens, or stimulants.

We find strong evidence that higher temperatures increase the incidence of violent crimes, assaults, and intimate partner violence involving any substance, alcohol, and drugs. When disaggregating by specific drug type, we find significant positive effects for crimes involving cocaine, marijuana, and stimulants, and imprecisely estimated for hallucinogens, whereas effects on heroin-related crimes are small and not significant across crime categories.

Fact 4: Substances amplify the effect of temperatures on crimes. Finally, we combine evidence on substance use, temperatures, and violent behavior to test whether the temperature-crime relationship varies with local measures of substance use. Figure 4 shows that the marginal effect of daily temperatures on violent crimes, assaults, and intimate partner violence cases is significantly larger in counties with higher opioid prescription rates, as measured during the pre-intervention period between 2006 and 2009. While only associational, these results suggest that substance use can amplify the psychological and physiological effects of higher temperatures on aggressions.

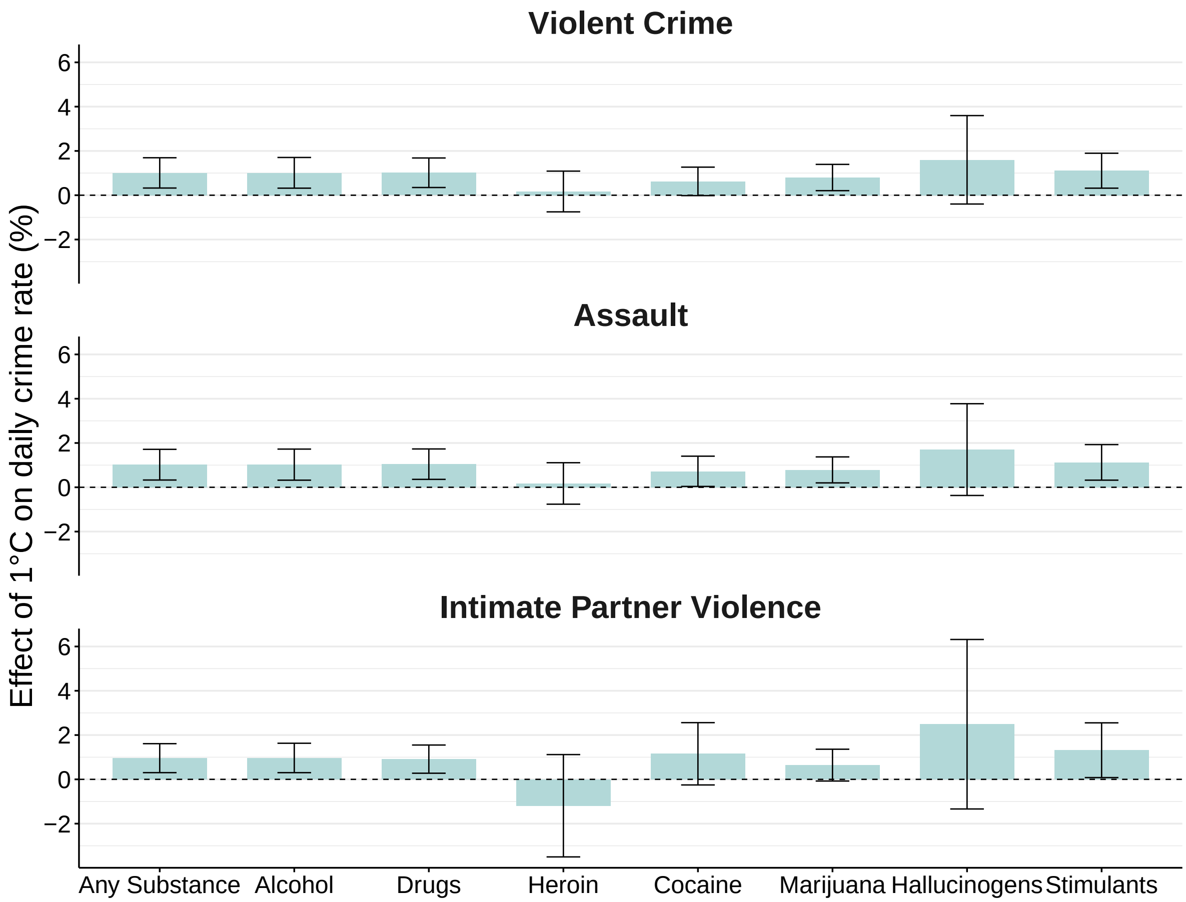
Collectively, these four empirical patterns point to substance use as a key mechanism linking temperatures to interpersonal crime, motivating our analysis of how interventions that moderate substance abuse can attenuate this relationship.

4 Substance abuse treatment facilities

4.1 Empirical approach

In this section, we examine whether access to substance-abuse treatment (SAT) facilities mitigates the impact of temperature on crimes. We extend a traditional temperature–crime specification to identify the coefficient of an interaction term capturing how the temperature–crime

Figure 3: Effect of daily temperatures on substance-involved crimes



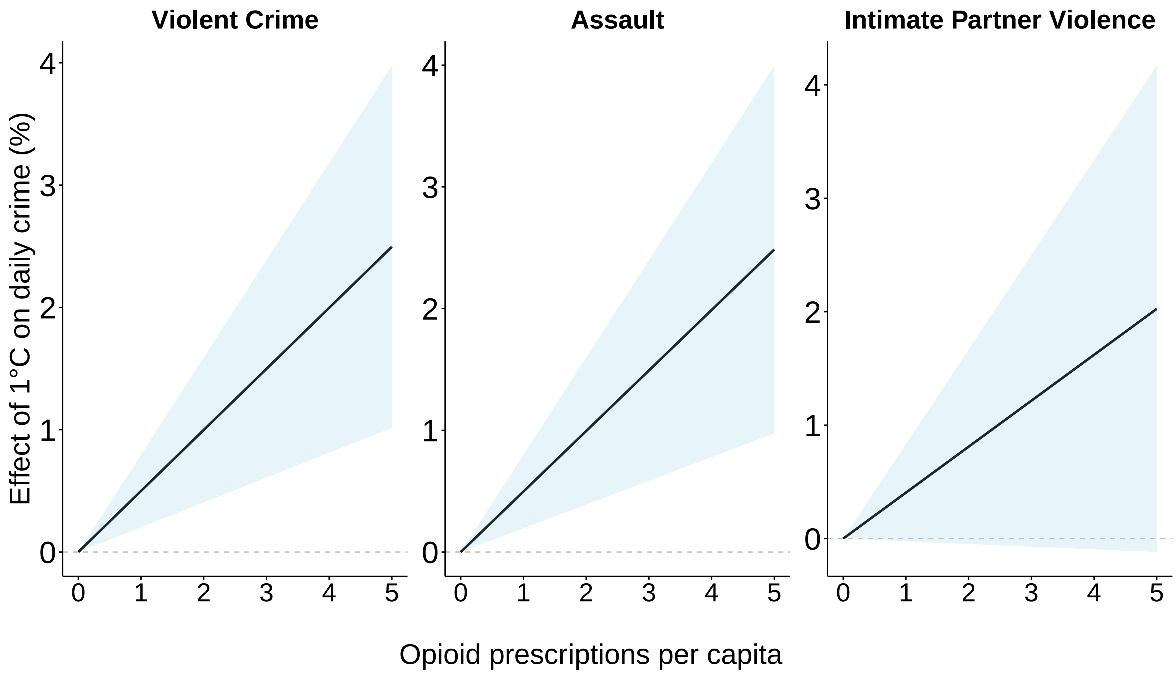
Notes: The figure plots the coefficients of temperature on crime rates per 100,000 people for different categories of crimes. The coefficients (in teal) are normalized by the weighted sample mean. The regressions control for daily total precipitation, and jurisdiction-month-year, day-of-year, week-of-year, and day-of-week fixed effects. Regressions are weighted by jurisdiction-location population. Confidence intervals at 95% are reported with standard errors clustered at the county-level.

elasticity varies with increasing access to treatment facilities. Our estimating equation is written as

$$\begin{aligned} Y_{idmt} = \quad & \beta\, T_{c(i)dmt} \times SAT_{c(i)t-1} + \gamma\, P_{c(i)dmt} \times SAT_{c(i)t-1} + \\ & + \delta_{c(i)} T_{c(i)dmt} + \theta_{c(i)} P_{c(i)dmt} + \delta_t T_{c(i)dmt} + \theta_t P_{c(i)dmt} + \\ & + \mu_{imt} + \phi_{dt} + \kappa_{dw} + \lambda_{wt} + \varepsilon_{idmt}, \end{aligned} \tag{1}$$

where Y_{idmt} denotes the number of reported crimes per 100,000 people in jurisdiction i on day d, month m, and year t. Daily average temperature ($T_{c(i)dmt}$) and total precipitation ($P_{c(i)dmt}$) are at the county level c. $SAT_{c(i)t-1}$ captures the number of SAT facilities per 100,000 people

Figure 4: Effect of temperature on daily crime rate by county-level opioid prescriptions



Notes: The figure plots the predicted effect of daily temperatures on daily crime rates (expressed in %, relative to the mean) over population-weighted mean per capita opioid prescriptions. Estimates are obtained from a regression that controls for precipitation interacted with county-level opioid prescriptions, and for jurisdiction-month-year, day-of-year, week-of-year and day-of-week fixed effects. Shaded areas show 95% confidence intervals with standard errors are clustered at the county level.

in a county, lagged one year to ensure that openings precede observed crime outcomes. All regressions are weighted by population in the jurisdiction, and we cluster standard errors at the county-level.

Our coefficient of interest, β, captures how the temperature-crime relationship varies with access to treatment, by comparing how the sensitivity of crime to daily temperature fluctuations changes within counties over time as access to substance-abuse treatment changes. We include jurisdiction-month-year fixed effects, μ_{imt}, that absorb differences in crime seasonality within each jurisdiction for a given month-year (e.g., Chicago Police Department in September 2013); day-of-year fixed effects, ϕ_{dt}, that capture nationwide shocks common to all jurisdictions in a given day (e.g., September 1st); day-of-week fixed effects, κ_{dw}, that account for systematic intra-week variation in criminal activity and reporting practices (e.g., Saturday); and week-of-year fixed effects, λ_{wt}, that also absorb unobserved differences common across jurisdictions in a month across weeks.[11] Since there might be residual unobserved differences in how temperature affects crime across time or space that are correlated with the opening of new SAT facilities, we flexibly allow for the effect of temperature and precipitation to vary by county (e.g., temperatures in Los Angeles County and in Cook County have different effects regardless of policy changes), and by year (e.g., temperatures in 2002 and 2012 have different effects nationwide).

Finally, a potential concern is that changes in substance abuse treatment facilities may themselves respond to local temperatures or be endogenous to places more exposed to opioid prescriptions. We show that the number of SAT facilities (and facilities per capita) does not depend on temperature nor opioid exposure, alone or interacted with the post-reformulation period (Table E1). These results suggest that variation in SAT facilities is orthogonal to temperature and exposure to opioids, supporting the interpretation of SAT facilities as plausibly exogenous variation of the temperature–crime relationship rather than endogenous responses to it.

Altogether, identification of β comes from within-jurisdiction-month-year variation in weather, effectively comparing, for instance, how crimes in Los Angeles respond to daily temperature fluctuations before and after the opening of a SAT, accounting for other temporal factors that are common across jurisdictions that correlate with within-month-year variation in the daily temperature–crime relationship by day of the week, day of the year, and week of the year.

4.2 Results

Figure 5 presents normalized point estimates relative to the average number of crimes in counties without any SAT establishments during the sample period (tabular results are reported in Table E3). We find that opening one additional SAT establishment per 100,000 people reduces the effect of a 1°C increase in temperature on total violent crime by 0.0008 incidents per 100,000 people — equivalent to about 0.18% of the daily average violent crime

[11] Because the number of SAT facilities varies at the county–year level, the direct effect of SAT facilities on violent crime cannot be estimated in our baseline specification. In Appendix E, we describe and show the results from a less conservative specification that leverages interannual variation and allows us to identify the direct effect of SAT facilities on crime.

rate in counties without any establishments. The mitigating effect of SATs is similar in magnitude for assaults and intimate partner violence, while it is smaller in magnitude (0.05%) for fraud crimes, allowing us to rule out effects in magnitude comparable to violent crimes. This result is consistent with our hypothesis that SAT facilities primarily reduce the effect of temperatures on crimes that involve physical interactions between victims and offenders.

Evaluated at the sample mean of 5.39 SAT establishments per 100,000 people, the implied reduction in the temperature–violent crime relationship is roughly 1% of the daily average violent crime rate in counties without any establishments. Similarly, the implied reduction in the temperature-IPV relationship is approximately 0.9%. Using estimates from a regression that identifies the average treatment effect of temperature on violent crimes (Table E2, Panel B), we find that opening an additional SAT offsets approximately 20% of the temperature effect (0.0027).

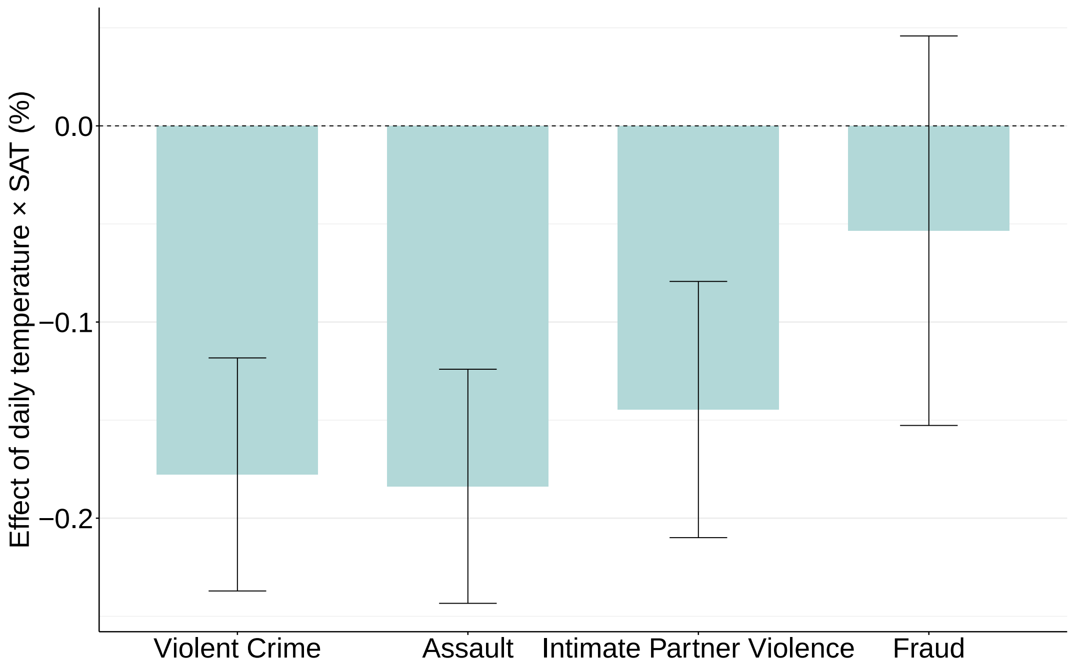
Robustness. We conduct several robustness checks, reported in Appendix E. First, we include in the sample counties not reporting any SAT facility between 1998 and 2016 (Table E5); results remain similar and, if anything, slightly larger in magnitude and more precise. Second, restricting the sample to agencies reporting crimes in every month yields similar estimates (Table E6). Third, redefining treatment as the count of establishments in each county does not affect our estimates (Table E7), while defining it as the first-ever opening of a SAT facility prevalently produces statistically insignificant interaction effects, suggesting that the the mitigating effect primarily operates along the intensive rather than the extensive margin (Table E8). Finally, we test the sensitivity of our findings to alternative fixed effects (Table E2, see Appendix E.1 for details).

5 Opioid reformulation

5.1 Empirical approach

Our second specification aims at quantifying the extent to which the OxyContin reformulation in 2010 reduced the impact of temperatures on crimes by attenuating the physiological

Figure 5: Effect of substance abuse treatment facilities on temperature-crime relationship



Notes: The figure plots the coefficients from the interaction term between average daily temperature and number of substance abuse treatment (SAT) facilities per 100,000 people in a regression where the outcome variable is the number of crimes per 100,000 people. The coefficients are normalized using the average number of crimes in counties that have no SAT establishments. The sample is restricted to the period 1999-2017 and to counties with at least one establishment opened in the same period according to Census Business Patterns (CBP) dataset. The regression also controls for county- and year-specific temperature and precipitation coefficients, jurisdiction-month-year, day-of-year, week-of-year, and day-of-week fixed effects. Regressions are weighted by jurisdiction-location population. Confidence intervals at 95% are reported with standard errors clustered at the county-level.

consequences of substance abuse. Since this policy was mandated across the entire U.S. in 2010, we design a specification akin to a triple difference, combining temperature variation with pre-reformulation cross-sectional county-level exposure to prescription opioids before and after the policy. Our baseline specification is

$$\begin{aligned} Y_{idmt} = \quad & \beta_1 T_{c(i)dmt} \times \text{Opioid exposure}_{c(i)} + \beta_2 T_{c(i)dmt} \times \text{Opioid exposure}_{c(i)} \times \mathbf{1}_{t \geq 2010} + \\ & + \gamma_1 P_{c(i)dmt} \times \text{Opioid exposure}_{c(i)} + \gamma_2 P_{c(i)dmt} \times \text{Opioid exposure}_{c(i)} \times \mathbf{1}_{t \geq 2010} + \\ & + \delta_t T_{c(i)dmt} + \delta_s T_{c(i)dmt} + \theta_t P_{c(i)dmt} + \theta_s P_{c(i)dmt} + \\ & + \mu_{imt} + \phi_{dt} + \kappa_{dw} + \lambda_{wt} + \varepsilon_{idmt}, \end{aligned} \tag{2}$$

where we interact daily average temperature $T_{c(i)dmt}$ and total precipitation $P_{c(i)dmt}$ with county-level pre-2010 exposure to prescription opioids (Opioid exposure$_{c(i)}$), as measured by the population- weighted average number of Schedule II opioid prescriptions per capita, and an indicator variable which takes value of one for the post-reformulation period, starting from 2010 ($\mathbf{1}_{t\geq 2010}$). The remainder of the specification is similar to Equation 1, with jurisdiction-month-year, day-of-year, week-of-year, and day-of-week fixed effects, and allowing for year-specific and state-specific direct impacts of temperatures and precipitation.

Our specification allows us to identify the change in the temperature-crime relationship between high- and low-opioid exposure counties before and after the reformulation, while exploiting within month-year variation in temperatures and crimes in a given jurisdiction, and accounting for annual and state-specific differences in the direct effects of meteorological conditions on crimes.

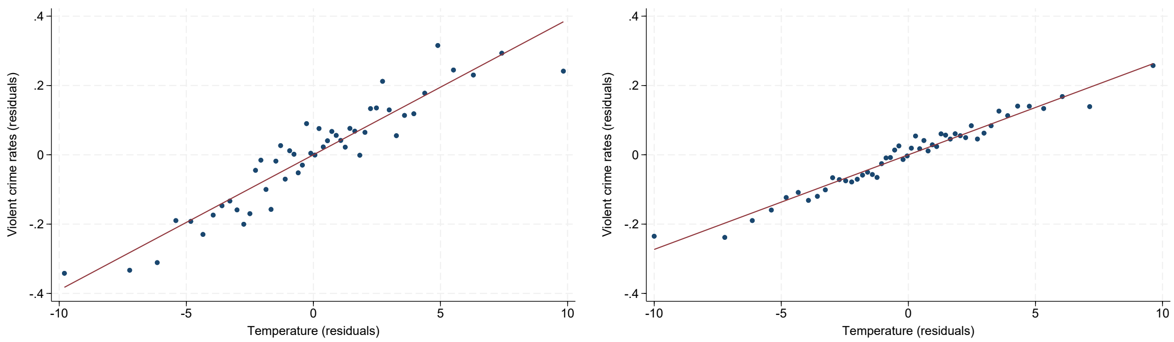
While our identifying assumption is fundamentally untestable, we provide additional indirect tests to support its plausibility. To rule out any potential differential pre-intervention trends between high- and low-exposure counties to prescription opioids, we estimate dynamic treatment effects. First, we allow for temporal heterogeneous effects of the policy in a binned event study. We construct binary indicators that, respectively, distinguish i) pre-reformulation years (2006 to 2009); ii) years immediately following reformulation (2011-2013); iii) years 2014 to 2016 for medium-run impacts; and iv) years 2017 to 2023 for long-run impacts of the reformulation. Second, we estimate the role of opioid reformulation in the crime response to daily temperatures in a fully specific year-by-year event study specification. Thus, we identify differences in the temperature-crime relationship between counties with high and low pre-intervention exposure in a given year as compared to 2010.

5.2 Results

A preliminary visual inspection of the regression-adjusted relationship between temperature and violent crimes in the sample of counties with high opioid prescriptions (above sample median, 0.83) before and after the policy shows a substantial reduction of the slope of the gradient after the policy reformulation (Figure 6). This result suggests that the opioid reformulation has a mitigating effect on the relationship between temperature and violent crimes in counties with greater exposure to opioids.

Figure 6: Temperature and opioid exposure before and after the reformulation

(a) Pre-policy high opioid exposure counties **(b)** Post-policy high opioid exposure counties



Notes: Panels (a) and (b) show binned scatterplots with 50 bins and a linear regression on the underlying data. Each shows the correlation net of jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects between residualized violent crime rate and residualized daily temperatures. The panels show the relationship for counties with above-median exposure to prescription opioids in the sample: before the policy through 2006-2009 in Panel (a), and after the opioid reformulation through 2010-2023 in Panel (b).

We next examine the role of the opioid reformulation in mediating the temperature-crime relationship across crime types. Table 2 reports the estimates of the interaction between temperatures, opioid exposure, and the post-reformulation period (additional crime categories are reported in Table F1). The coefficient on the triple interaction term is negative and statistically significant for violent crimes, including assault, rape, homicide, and intimate partner violence, but not fraud. We find that a 1°C increase in daily temperature is associated with 0.034 fewer violent crime cases per 100,000 people after the 2010 reformulation. This corresponds to roughly an 11% reduction relative to the pre-reformulation average violent crime rate (0.304). The estimated effect offsets the pre-policy differential effect of temperatures in opioid-exposed counties, implying that the reformulation eliminated the amplified temperature sensitivity of crime in these areas that we documented in Section 3.

The magnitude is similar when we unpack by category of violent crimes: 11% for assaults, 6% for rapes, and 12% for homicides, and for violent crimes (assaults, rapes, and homicides) on female intimate partners (column 3). A 1°C increase in temperature is associated with 0.007 fewer IPV cases per 100,000 people post-reformulation, or about a 9% decline compared to the pre-policy mean (0.077). Comparing the magnitude of our triple interaction term to the heterogeneous effects of temperature by baseline opioid exposure, we find that the 2010 opioid reformulation effectively eliminated the additional compounding effect of opioid misuse on temperature-induced violent crime.

The attenuation is concentrated in interpersonal crimes, consistent with our hypothesis linking higher temperatures to aggressive behavior through physiological channels exacerbated by substance abuse and misuse. As discussed in Section 3, opioid misuse may exacerbate the discomfort, stress, and impulsivity induced by higher temperatures, through both reduced inhibition and increased withdrawal-related irritability. The 2010 reformulation reduced such misuse and was effective at mollifying the behavioral response of aggression to higher temperatures. In contrast, instrumental or economically motivated crimes like fraud or gambling (columns 8 and 9 in Table F1) do not respond to higher temperatures in higher opioid exposed counties nor to their reformulation.

Our triple difference research design allows us to look at the dynamic effect of the policy in moderating the temperature-violent crime relationship. In Figure 7, we report the effect on violent crimes. The left-hand side panel reports the same estimated coefficient in column 1 in Table 2, normalized by the average violent crime rate before the 2010 policy. The right-hand side panel shows the differential effects of the opioid reformulation in the pre-period (2006-2009), short-run period (2011-2013), medium-run period (2014-2016), and long-run period (2017-2023). The effect in the pre-policy time indicator is small in magnitude and not statistically significant at any conventional level, allaying concerns on differential pre-intervention trends. In the post-policy period, the short-, medium- and long-run effects are negative and statistically significant at the 95% level. The effects are marginally, but not significantly, smaller in magnitude over time, suggesting a temporally persistent effect of the policy in attenuating the effect of temperatures on violent crimes in counties with higher rates of opioid prescriptions.[12]

Figure 8 further unpacks the results and displays the estimates of the triple interaction

[12] We document similar patterns in other categories of crime (assaults, intimate partner violence, and frauds) in Figure F1. The policy persistently reduces the effect of temperatures in counties with higher exposure to opioids on assaults and violence in intimate contexts; whereas the effect is not statistically different from zero in the case of financially-motivated crimes that tend to require more preparation and planning, like frauds.

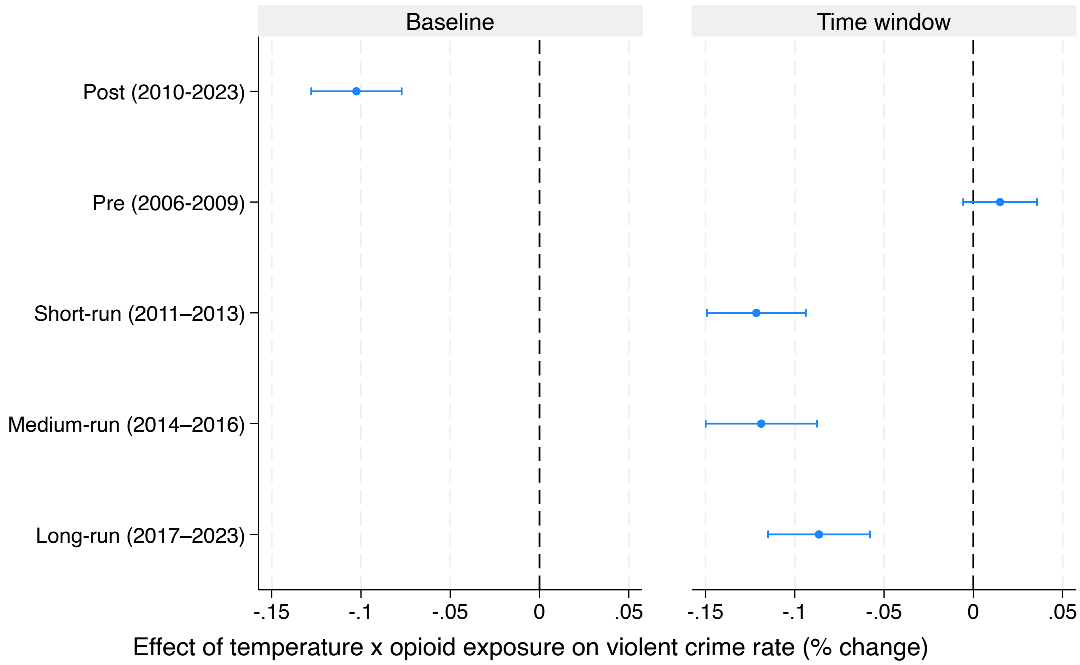
Table 2: Effects of opioid reformulation on temperature and crimes

	Daily crimes per 100,000 people			
	Violent crime (1)	Assault (2)	IPV (3)	Fraud (4)
Temperature × Opioid exposure	0.0336***	0.0329***	0.00686***	0.000488
	(0.00420)	(0.00410)	(0.00120)	(0.000963)
Temperature × Opioid exposure × Post-2010	-0.0341***	-0.0334***	-0.00696***	-0.000484
	(0.00414)	(0.00404)	(0.00119)	(0.000964)
Observations	38,033,629	38,033,629	38,033,629	38,033,629
Pre-policy outcome mean	0.304	0.294	0.077	0.068
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. *Post-2010* is a dummy variable equal to 1 for the post-reformulation period, starting from 2010. *Opioid exposure* is the county-level pre-2010 exposure to opioids. Standard errors are clustered at the county level. All regressions are weighted using jurisdiction population weights. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

term in an event study design, with 2010, the year in which OxyContin was reformulated, normalized to zero. Similarly, the estimated coefficients in the years prior to reformulation are statistically indistinguishable from zero. After the reformulation in 2010, for an increase in daily temperatures, the number of daily violent crimes, as well as of assaults and of intimate partner violence, decreases in high-exposure counties relative to low-exposure counties. The estimates confirm that the effect is persistent over time, and while smaller in magnitude after 2017, the policy is still effective 13 years after the reformulation. Given uncertainty around climate realizations, the persistence of sizable effects over more than a decade is crucial for a holistic assessment of substance regulation as an adaptation policy, whose benefits must be evaluated on a long-run horizon.

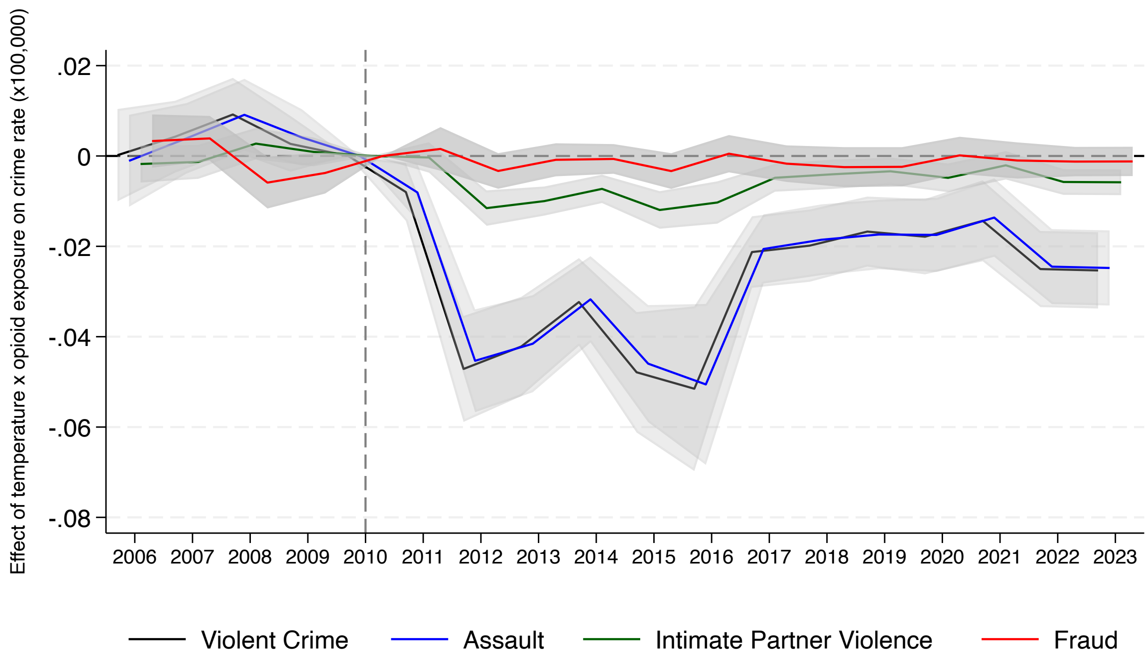
Figure 7: Dynamic effects of opioid reformulation on daily temperature-violent crimes



Notes: Each panel corresponds to a separate regression. The dependent variable is the daily crime rate per 100,000 inhabitants, normalized on the y-axis according to the average crime rate before 2010. On the left panel, the figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opioid prescription, and an indicator variable that takes the value of one for the post-reformulation years, 2010-2021. On the right panel, the triple interaction is with an indicator variable (short-run) equal to one for the years immediately following reformulation, 2011 to 2013, another one (medium-run) equal to one for the years 2014 to 2016, and another indicator variable (long-run) for the years 2017-2021 on the jurisdiction-level rate of violent crimes. The regression also controls for jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects, and state- and year-specific temperature and precipitation effects. Observations are weighted by the population in each jurisdiction. Bins represent the 95% confidence intervals with standard errors clustered at the county-level.

The responsiveness of the temperature-violent crimes relationship decreases in high-exposure counties resulting in an average relative decrease of 0.03 cases per 100,000 people/1°C/day. The dynamic estimates show that changes in the temperature–crime relationship become more pronounced starting in 2012, two years after implementation. A plausible explanation for this delay is that a sudden reduction in opioid access may initially trigger withdrawal, substitution toward other substances, or related disruptions that affect emotional stability in the short run (Pergolizzi Jr et al., 2020).

Figure 8: Event study of the differential effect of opioid reformulation on temperature-crime



Notes: The figure plots the coefficients associated with the triple interaction term between daily temperature, pre-intervention opioid exposure and year dummies in a regression where the outcome variable is the number of daily crimes (per 100,000 people) for four different categories of crimes. The regression also controls for jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects, and state- and year-specific temperature and precipitation effects. Shaded area represent the 95% confidence intervals with standard errors clustered at the county-level.

Robustness. Our results are robust to a plethora of tests that exclude the Covid-19 period after 2019 (Figure F2); cluster standard errors at the state level (Figure F3); aggregate the sample at the jurisdiction-month and county-day levels (Table F2); restrict the sample to certain seasons (Table F3); use alternative measures of exposure to opioids, including the number of opioid pills and the shipments per capita (Table F4); exclude agencies that do not report crimes for all the twelve months in a year in the entire sample (Table F5); use alternative fixed effects, accounting for jurisdiction by calendar-day, jurisdiction by month-year, and date (day-month-year) fixed effects (Table F6). The aggregation checks and alternative fixed effect specifications suggest that our results are not unlikely to be driven by unobservables absorbed by our fixed effects, allaying concerns on sample selection or alternative channels — such as endogenous crime reporting or police activity — confounding our estimated relationship.

6 Mechanisms and additional results

In this section, we explore potential channels through which substance abuse regulations can moderate the impact of temperature on violent crimes.

6.1 Interactions with other substances

Substance-involved crimes. A first mechanism operates through crimes committed under the influence of substances. We test whether the policies mitigate the effect of temperature by restricting the sample to cases where the offender was reported as under the influence. Panel A of Table 3 shows that the expansion of SAT facilities significantly reduces the temperature–violent crime gradient for substance-involved crimes. The largest reductions occur in alcohol-related cases, consistent with alcohol being the most common reason for treatment admission (about 40%) and with evidence that alcohol consumption and hotter temperatures are complements. By contrast, we detect no effects for crimes involving heroin, cocaine, or marijuana (columns 3-5), where estimates are small and imprecise. Panel B reports the effects of the OxyContin reformulation. Because opioid misuse is often combined with complementary substances (Compton et al., 2021), limiting access to abusable opioids could indirectly affect behaviors sensitive to higher temperatures. We find that the reformulation substantially reduced the temperature sensitivity of both any-substance and alcohol-involved crimes, suggesting a decline in complementary alcohol use. For other substance, the reformulation had no statistically significant nor economically meaningful effect. While we cannot rule out substitution toward these substances, our results suggest that any such shift does not appear to strengthen the temperature-crime relationship involving these substances.[13]

Access to Fentanyl from Mexico. At the time of the 2010 OxyContin reformulation, fentanyl — a synthetic opioid approximately fifty times more potent than heroin — had become a readily available substitute, with much of its supply trafficked across the U.S.–Mexico border by Mexican criminal organizations (Evans et al., 2019) and frequently found in counterfeit pills (Drug Enforcement Administration, 2020). We explore whether the effectiveness of the opi-

[13]Results for both policies are similar for assault (Table F7) and intimate partner violence (Table F8) cases involving substances.

Table 3: Effects of substance abuse regulation policies on temperature-violent crimes involving substances

	Violent crimes per 100,000 people involving substances				
	Any substance (1)	Alcohol (2)	Heroin (3)	Cocaine (4)	Marijuana (5)
Panel A: SAT facilities					
Temperature × SAT	-0.0001***	-0.0001***	-0.000001	-0.000002	-0.000001
	(0.00003)	(0.00003)	(0.0000005)	(0.000001)	(0.000002)
Mean Outcome	0.0716	0.0671	0.00002	0.0001	0.0007
Observations	26,879,916	26,879,916	25,367,771	25,367,771	25,367,771
Panel B: Opioid reformulation					
Temperature × Opioid exposure	0.0058***	0.0057***	0.00000128	-0.0000116	0.0000559
	(0.00000668)	(0.0000284)	(0.0000416)	(0.0004)	(0.0004)
Temperature × Opioid exposure × Post-2010	-0.0059***	-0.0058***	-0.00000156	0.0000121	-0.0000558
	(0.00000669)	(0.0000284)	(0.0000416)	(0.0004)	(0.0004)
Pre-policy mean outcome	0.0382	0.0353	0.00001	0.0001	0.0004
Observations	38,033,629	38,033,629	35,768,587	35,768,587	35,768,587

Notes: Table reports on our baseline specifications, respectively Equation (1) and Equation (2) in Panel A and B on the number of violent crimes involving substances in a jurisdiction per 100,000 people. Panel A controls for jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects, and state- and year-specific temperature and precipitation effects. In Panel A "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. All regressions are weighted using jurisdiction population weights. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

oid reformulation depends on geographic access to these illicit substitutes, using the distance to the nearest legal U.S.–Mexico border crossing as a proxy for potential access to trafficked fentanyl-laced products.[14]

We find that the reformulation's effect is significantly stronger in counties farther from the border (Table 4). The policy reduces the temperature impact on violent crimes by approximately 3% in counties below the median distance to the U.S.-Mexico border (column 1), compared to a 17% reduction in counties above the median (column 2). We find similar results also for assaults and intimate partner violence cases (columns 3-6). Although these results are associational and may be subject to sample selection issues with other confounding factors varying with distance from the border, they suggest that geographic access to illegal opioid

[14]We measure distance between each county's population centroid and U.S.–Mexico border crossings, obtained from the Bureau of Transportation Statistics (BTS, 2024). We restrict the sample to crossings accessible by pedestrians, private vehicles, or buses, and compute travel distances from the population centroid of each county to the nearest crossing.

substitutes may attenuate the effectiveness of the opioid reformulation.

Table 4: Effects of substance abuse regulation policies on temperature-crimes by distance from U.S.-Mexico border

	U.S.-Mexico closest border crossing distance					
	Violent Crime		Assault		Intimate Partner Violence	
	Below median	Above median	Below median	Above median	Below median	Above median
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × Opioid exposure	0.0100**	0.0373***	0.0103**	0.0365***	0.00275*	0.00699***
	(0.00509)	(0.00563)	(0.00508)	(0.00549)	(0.00157)	(0.00152)
Temperature × Opioid exposure × Post-2010	-0.0106**	-0.0308***	-0.0108**	-0.0302***	-0.00284*	-0.00574***
	(0.00501)	(0.00530)	(0.00500)	(0.00515)	(0.00155)	(0.00154)
Pre-policy mean outcome	3.996	0.183	3.848	0.177	1.113	0.043
Observations	19,026,961	19,006,668	19,026,961	19,006,668	19,026,961	19,006,668

Notes: The outcome variable is the number of violent crimes (in columns 1-2), of assaults (in columns 3-4), and of intimate partner violence on females (in columns 5-6) in a jurisdiction per 100,000 people. All columns control for jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects, and state- and year-specific temperature and precipitation effects. All regressions are weighted using jurisdiction population weights. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

6.2 Interactions with other substance-related policies

We also explore how substance abuse regulations interact with other policies governing access to substances. We study whether legal access to medical marijuana mediates the effects of the SAT expansion and the OxyContin reformulation on the temperature–crime relationship through therapeutic substitution. Prior work shows that medical marijuana availability can reduce dependence on more harmful substances and lower opioid misuse and overdose deaths (Powell et al., 2018). If medical marijuana provides a legal substitute, the response to substance abuse regulation should be more stronger in states without such laws, where legal substitutes are more limited.

Table 5 provides evidence consistent with this hypotheses. Both the expansion of SAT facilities (Panel A) and the OxyContin reformulation (Panel B) attenuate the temperature-crime gradient only in states without medical marijuana laws (columns 1-3-5).[15] In contrast, when medical marijuana is legally accessible, we do not detect a statistically significant effect of substance abuse regulation on the crime sensitivity to temperature. Consistent with a substitution interpretation, the double interaction between temperature and opioid prescriptions is small and statistically indistinguishable from zero in states with medical marijuana laws, but

[15]We observe similar patterns for other crime categories (Table F9).

positive and significant where such access is absent. Although these results are associative, they suggest that medical marijuana availability may shift consumption away from opioids and more dangerous substances, thereby attenuating the co-benefits of substance abuse regulation for temperature-related crime.

Table 5: Effects of substance abuse regulation policies on temperature-crimes in states with medical marijuana laws.

	Medical Marijuana Law in U.S. States					
	Violent Crime		Assault		Intimate Partner Violence	
	Without	With	Without	With	Without	With
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: SAT facilities						
Temperature × SAT	-0.0009***	0.0002	-0.0009***	0.00009	-0.0002***	0.00004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00005)	(0.00009)
Mean Outcome	3.085	0.067	2.974	0.065	0.821	0.019
Observations	21,931,688	4,948,228	21,931,688	4,948,228	21,931,688	4,948,228
Panel B: Opioid reformulation						
Temperature × Opioid exposure	0.0433***	-0.000101	0.0424***	0.0000895	0.00974***	-0.00167
	(0.00497)	(0.00873)	(0.00483)	(0.00866)	(0.00143)	(0.00292)
Temperature × Opioid exposure × Post-2010	-0.0435***	-0.000961	-0.0426***	-0.00114	-0.00976***	0.00148
	(0.00495)	(0.00832)	(0.00482)	(0.00826)	(0.00143)	(0.00281)
Pre-policy mean outcome	0.205	4.287	0.198	4.143	0.051	1.291
Observations	26,394,328	7,144,196	26,394,328	7,144,196	26,394,328	7,144,196

Notes: The outcome variable is the number of violent crimes (in columns 1-2), of assaults (in columns 3-4), and of intimate partner violence on females (in columns 5-6) in a jurisdiction per 100,000 people. Columns 1-3-5 report estimates obtained using the sample of jurisdictions in states where there is no legal access to medical marijuana, columns 2-4-6 report estimates obtained using the sample of jurisdictions in states where there is legal access to medical marijuana. Panel A controls for jurisdiction-month-year, day-of-week, day-of-year, and week-of-year fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-month-year, day-of-week, day-of-year, and week-of-year fixed effects, and state- and year-specific temperature and precipitation effects. In Panel A "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. All regressions are weighted using jurisdiction population weights. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

6.3 Alternative mechanisms

We test for a set of alternative mechanisms that may explain the effectiveness of substance abuse policies in mitigating the temperature effects on crime.

Biophysical adaptation. Our results indicate that by reducing substance abuse, both the expansion of SAT facilities and the 2010 opioid reformulation dampen the behavioral response to higher temperatures, mitigating the rise in impulsivity, aggression, and intoxication that would otherwise increase with temperatures. A potential complementary mechanism is that the crime response to temperature through substance abuse depends on local climatic conditions. In persistently hotter areas, individuals may be physiologically acclimated such that the compounding effect of temperature and substance abuse on violent behavior — and hence the moderating role of substance abuse regulation — is weaker.

We test this hypothesis by estimating differential effects of the temperature-policy interaction by climate. Table 6 reports results for SAT facilities (Panel A) and for the opioid reformulation (Panel B). In both cases, the effects of substance abuse regulation policies are larger and statistically significant only in counties in the coldest tercile of average temperature. In Panel B, the temperature-opioid exposure double interaction term is not significant in hot counties, suggesting that there is no evidence of the compounding effect of temperature and substance abuse in climates where biophysical adaptation is likely strongest, and thus policies mitigating this channel have also limited effect.

Table 6: Effects of substance abuse regulation policies on temperature-crimes by climatic areas

	Climatic areas								
	Violent Crime			Assault			Intimate Partner Violence		
	Cold	Temperate	Hot	Cold	Temperate	Hot	Cold	Temperate	Hot
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: SAT facilities									
Temperature × SAT	-0.0003***	-0.0003	-0.0002	-0.0003***	-0.0004	-0.0003	-0.00007*	-0.0002**	-0.00003
	(0.0001)	(0.0003)	(0.0004)	(0.0001)	(0.0003)	(0.0004)	(0.00004)	(0.00009)	(0.0002)
Mean Outcome	0.126	2.632	5.037	0.120	2.536	4.901	0.032	0.733	1.361
Observations	13,250,591	8,521,014	5,108,311	13,250,591	8,521,014	5,108,311	13,250,591	8,521,014	5,108,311
Panel B: Opioid reformulation									
Temperature × Opioid exposure	0.0339***	0.0150***	0.00347	0.0332***	0.0147***	0.00335	0.00518**	0.00225*	0.000596
	(0.00880)	(0.00506)	(0.00628)	(0.00857)	(0.00488)	(0.00627)	(0.00213)	(0.00136)	(0.00204)
Temperature × Opioid exposure × Post-2010	-0.0385***	-0.00573	-0.00375	-0.0381***	-0.00577*	-0.00361	-0.00567***	0.0000619	-0.000636
	(0.00551)	(0.00363)	(0.00619)	(0.00544)	(0.00347)	(0.00618)	(0.00154)	(0.00123)	(0.00202)
Pre-policy mean outcome	0.094	3.331	5.191	0.090	3.223	5.043	0.021	0.804	1.448
Observations	12,684,691	12,671,184	12,677,754	12,684,691	12,671,184	12,677,754	12,684,691	12,671,184	12,677,754

Notes: Table reports on our baseline specifications, respectively Equation (1) and Equation (2) in Panel A and B on the sub-sample of counties split by tercile of the mean temperature in the sample. The outcome variable is the number of violent crimes (in columns 1-3), of assaults (in columns 4-6), and of intimate partner violence on females (in columns 7-9) in a jurisdiction per 100,000 people. Panel A controls for jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-month-year, day-of-year, day-of-week, and week-of-year fixed effects, and state- and year-specific temperature and precipitation effects. All regressions are weighted using jurisdiction population weights. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Time of the day. We also examine whether substance abuse regulation policies mitigate the effect of temperatures on crime at different times of day. Opioid abuse impairs both sleep duration and quality (Bertz et al., 2019), and higher nighttime temperatures can disrupt sleep and increase the likelihood of insufficient sleep (Minor et al., 2022; Obradovich et al., 2017). These combined effects may reduce individuals' ability to manage stress, increasing the probability of aggressive responses to aversive stimuli generated by higher temperatures and substance use (Rauer and El-Sheikh, 2012). Using intra-daily temperature variation and the reported time of crime occurrence, we estimate separate effects for crimes in the morning, afternoon, evening, and night (Table E9 and Table F10). We find that both policies reduce the temperature sensitivity of violent crimes, assaults, and intimate partner violence across all times of day, but effects are largest in the evenings and at nights. For example, while the opioid reformulation reduces the impact of temperatures on violent crimes in the morning and afternoon by 7% and 7.6% relative to their pre-policy mean, violent crimes in the evening and at night are reduced by 15.5% and 13.6%. These results are consistent with the policies potentially mitigating the sleep-deprivation channel through which substance abuse harms are exacerbated at higher temperatures.

Day of the week. Because changes in time use are plausible mechanisms, the effectiveness of policies moderating substance abuse may vary across contexts where these behaviors are most pronounced. In particular, weekends provide greater flexibility to adjust routines and are associated with higher consumption of alcohol (Kuntsche and Labhart, 2012; Studer et al., 2014; Voas et al., 2013) and opioids (Spiller et al., 2010; Yan and Kuo, 2019). We find suggestive evidence that both the SAT expansion and the 2010 opioid reformulation are more effective at reducing crimes during weekends, when the behavioral channel through time use, social interactions, and substance consumption is most salient (Table E10 and Table F11).

Characteristics of crime. We also examine differential effects of the policy across crime characteristics, including use of firearm and location of crime. Our estimates indicate that the expansion of SAT facilities is significantly more effective in reducing violent crime, assault, and intimate partner violence not involving firearms (Table E11, columns 1–2). In contrast, for the OxyContin reformulation we find no statistically significant differences in its mitigating effect on temperature-related violent crimes and assaults between firearm and non-firearm incidents. For intimate partner violence, however, the reformulation is associated with a significant reduction only in temperature-induced crimes not involving firearms (Table F12, columns 1–2). Turning to information on the location of crimes, both policies primarily reduce the temperature sensitivity of offenses occurring indoors and at home, with the largest effects for intimate partner violence (Table E11 and Table F12, columns 4 and 6).

7 Monetizing social benefits of substance-abuse policies in a warming climate

Our estimates show that policies targeting substance abuse can generate substantial ancillary social benefits by attenuating the sensitivity of violent crimes to temperature. This mechanism is particularly salient in this context, where existing evidence find little scope for adaptation that has meaningfully mitigated the temperature-crime relationship (Burke et al., 2024). From a climate adaptation perspective, ignoring these co-benefits may understate the net social returns of policy interventions that indirectly mitigate climate impacts (Carleton et al., 2024). A natural question is whether the implied benefits are economically meaningful and how they compare, in magnitude, to both alternative crime-reduction policies and other successful adaptation interventions.

We focus on intimate partner violence (IPV), one of the most prevalent forms of violent crime in the United States (approximately 18% of all violent crimes) and with substantial social costs largely due to long-run health and productivity losses. Following Peterson et al. (2018), we assign a lifetime social cost of $135,556 (in $2023) per IPV case. We then compute the annual social costs associated with a 1°C increase in temperatures in the U.S. under four scenarios: (i) no adaptation; (ii) accounting for climate adaptation benefits and costs — via heterogeneous temperature responses across terciles of long-run average climate (Carleton et al., 2022, 2024); (iii) accounting for the expansion of substance abuse treatment facilities; and (iv) accounting for the abuse-deterrent reformulation of OxyContin. These monetary estimates are summarized in Figure 9, and we report the estimated annual number of IPV cases in the different scenarios in Figure G1.

Absent any margin of adaptation, and using the baseline temperature-IPV relationship estimated in Section 3, we find that a 1°C increase in temperatures induces 508 additional cases of intimate partner violence per year, corresponding to social costs of approximately

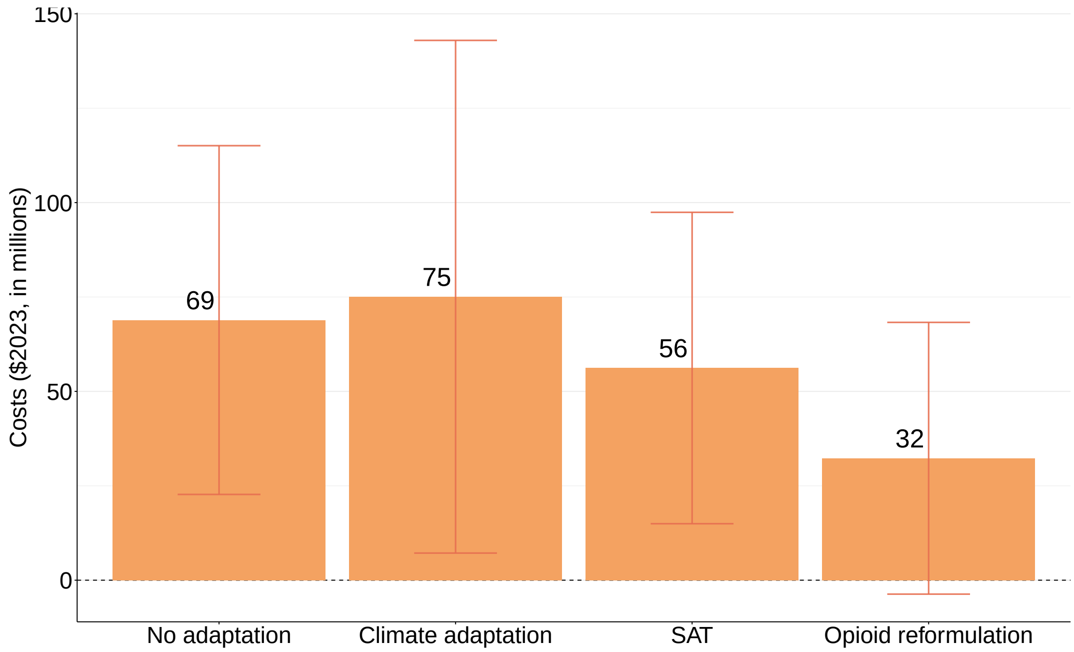
$69 million annually (95% CI: [$23, $115]). Allowing for climate adaptation yields similar cost estimates ($75 millions). This result, in line with prior climate-crime reviews (Burke et al., 2015, 2024), but in contrast with evidence of adaptation for other outcomes, such as mortality (Carleton et al., 2022), suggests that the physiological and psychological channels linking temperature to violent behavior remain largely unmitigated. We next quantify how substance abuse policies alter these temperature-induced social costs of IPV. Accounting for the expansion of SAT facilities reduces the annual social cost of a 1°C increase in temperatures to $56 million, approximately 80% of the cost implied by the no-adaptation benchmark. The abuse-deterrent opioid reformulation generates even larger gains: the implied annual net benefit is approximately $37 million, corresponding to approximately 270 avoided IPV cases per year attributable to a 1°C increase in temperature (see Figure G1).

To examine the economic significance of these magnitudes, we benchmark the implied welfare gains against other crime-reduction and climate adaptation policies in the United States. The estimated net benefits of the policies are comparable to the creation of 93 new mental healthcare facilities, based on evidence that opening an additional facility reduces crime costs by approximately $527,000 per year (Deza et al., 2022). Using monetary estimates of climate adaptation interventions, the residential AC expansion in the late 20th century generated approximately $4.25 billion benefits annually in reduced mortality (Barreca et al., 2016), and more restrictive gun laws are estimated to yield annual social benefits of a similar order of magnitude, about $3.38 billion per 1°C, by reducing temperature-driven homicides (Colmer and Doleac, 2023).[16]

We also compare the welfare gains of the policies to fiscal costs of key U.S. federal programs addressing opioid abuse and domestic violence. Our cumulative net benefits are equivalent to 27% of the annual funding for the Comprehensive Addiction and Recovery Act (CARA), 1.5% of the annual budget for the Violence Against Women Act (VAWA), and 93%

[16]In the latter case, the number of avoided homicides if more-prohibitive gun laws were in place is 299, comparable to the total number of avoided temperature-induced IPV implied by substance abuse policies for a 1°C increase (363; Figure G1). The difference in monetized benefits primarily reflects the higher assumed social cost of homicide ($11.3 million) relative to cases of intimate partner violence (McCollister et al., 2010).

Figure 9: Social Costs of Intimate Partner Violence from a 1°C increase in temperature



Notes: The figure reports estimated annual social costs of intimate partner violence induced by a 1°C increase in temperature, expressed in 2023$ (millions). Although outcome and climate data are available until 2023, estimates are based on the 2006-2017 sample, when information on substance abuse treatment (SAT) facility availability is observed and prior to the opioid reformulation we lack measures of prescription opioid exposure. Restricting the sample to this period ensures comparability across the four specifications. The "No adaptation" bar reflects the estimated direct effect of temperature on IPV. The "Climate adaptation" bar allows the temperature-IPV relationship to vary by terciles of long-run average temperature. The "SAT" bar incorporates both the direct temperature effect and its interaction with SAT expansion (Equation 1). The "Opioid reformulation" bar is based on estimates from Equation 2. Error bars denote 95% confidence intervals.

of the funding allocation to the Family Violence Prevention and Services Act (FVPSA).[17]

While these calculations underscore potentially large welfare gains from addressing substance abuse as a channel for mitigating the effects of rising temperatures on violent crime, they still represent an incomplete welfare assessment of both policies for two main reasons.

First, we do not conduct a full cost-benefit analysis or compute the marginal value of public funds (Hendren and Sprung-Keyser, 2020), since doing so would require comprehensive

[17]The Comprehensive Addiction and Recovery Act, signed into law in 2016, allocates about $181 million (in $2023) each year to fund programs that fight the opioid epidemic (see here for more information). The Violence Against Women Act, approved in 1994 and reauthorized in 2022, provides about $3.28 billion to create and support comprehensive, cost-effective responses to domestic violence, sexual assault, dating violence and stalking (see here for more information). The Coronavirus Aid, Relief, and Economic Security (CARES) Act included $52.99 million of supplemental funding to address domestic violence under the 1984 Family Violence Prevention and Services Act Program (see here for more information).

measurement of direct and indirect policy costs. Existing evidence suggests that the SAT expansion is relatively costly, with annual operating costs for a residential facility estimated approximately at $1.3 million (Alexandre et al., 2003), while the opioid reformulation involved more limited direct public expenditures. Prior work work finds that the reformulation reduced opioid abuse, yielding approximately $535 million in healthcare cost savings, and increasing healthcare expenditures by only $145 million over a 5-year time period (Kumar et al., 2019). In addition, it produced indirect social benefits in the form of roughly $476 million in workplace cost savings from reductions in premature deaths, lost wages, absenteeism, and disability per year (Kirson et al., 2014), but also additional social costs, including substitution toward heroin use (Evans et al., 2019), and increases in child physical abuse and neglect (Evans et al., 2022). Because these studies do not monetize the associated welfare losses, a comprehensive welfare accounting remains infeasible. Nevertheless, limiting our attention to the monetary components that are quantified in prior work, our results suggest that the opioid reformulation generated additional social benefits of approximately $37 million per year through reductions in temperature-induced IPV, about 6% of previously documented net social benefits.

Second, our monetization captures only the IPV-related component of temperature-induced crime. We focus on intimate partner violence because it is the most prevalent violent crime and because credible lifetime cost estimates are available. This should be viewed as a lower bound on the net benefits of substance abuse regulation, since our empirical results show that other categories of violent crime respond to temperature and are similarly moderated by these policies. As such, our results demonstrate a novel and economically meaningful channel through which substance abuse regulation mitigates the social damages of temperature increases.

8 Conclusions

This paper shows that policies not explicitly designed to address climate adaptation can meaningfully alter the relationship between temperature and violent behavior. Using thirty years of daily administrative crime data across the United States and combining multiple quasi-experimental research designs, we show that two major interventions aimed at reducing substance abuse—the expansion of substance abuse treatment (SAT) facilities and the reformulation of OxyContin— substantially attenuate the temperature sensitivity of violent crimes.

Our results highlight that efforts to reduce substance abuse can yield ancillary adaptation benefits by reducing temperature-driven crime. To our knowledge, these welfare gains have never been incorporated into cost–benefit assessments of substance-abuse. Yet, when comparing our back-of-the-envelope calculations to large-scale violence-prevention and public-health investments, the net social benefits of the policies are economically meaningful. Integrating social policy externalities is crucial for a holistic approach to cost benefit analysis of climate adaptation policies.

References

Adhvaryu, A., T. Molina, A. Nyshadham, and J. Tamayo (2024). Helping Children Catch Up: Early Life Shocks and the PROGRESA Experiment. *The Economic Journal 134*(657), 1–22.

Aizer, A. (2010). The gender wage gap and domestic violence. *American Economic Review 100*(4), 1847–1859.

Alexandre, P. K., M. C. Roebuck, M. T. French, and M. Barry (2003). The cost of residential addiction treatment in public housing. *Journal of substance abuse treatment 24*(4), 285–290.

Alpert, A., W. N. Evans, E. M. Lieber, and D. Powell (2022). Origins of the opioid crisis and its enduring impacts. *The Quarterly Journal of Economics 137*(2), 1139–1179.

Anderberg, D., H. Rainer, J. Wadsworth, and T. Wilson (2016). Unemployment and domestic violence: Theory and evidence. *The Economic Journal 126*(597), 1947–1979.

Anderson, C. A. (1987). Temperature and aggression: effects on quarterly, yearly, and city rates of violent and nonviolent crime. *Journal of personality and social psychology 52*(6), 1161.

Anderson, C. A. (2001). Heat and violence. *Current directions in psychological science 10*(1), 33–38.

Angelucci, M. and R. Heath (2020). Women empowerment programs and intimate partner violence. In *AEA Papers and Proceedings*, Volume 110, pp. 610–614.

Arteaga, C. and V. Barone (2026). Republican support and economic hardship: The enduring effects of the opioid epidemic. *The Quarterly Journal of Economics 141*(1), 499–558.

Avdeenko, A. and M. Frölich (2025). Cost and Benefits of Climate Change Adaptation Policies: Evidence from an RCT and Extreme Flooding in Pakistan. *Journal of the European Economic Association*, jvaf012.

Banerjee, R. and R. Maharaj (2020). Heat, infant mortality, and adaptation: Evidence from India. *Journal of Development Economics 143*, 102378.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy 124*(1), 105–159.

Barron, K., C. D. Parry, D. Bradshaw, R. Dorrington, P. Groenewald, R. Laubscher, and R. Matzopoulos (2024). Alcohol, violence, and injury-induced mortality: Evidence from a modern-day prohibition. *Review of Economics and Statistics 106*(4), 938–955.

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

Baysan, C., M. Burke, F. González, S. Hsiang, and E. Miguel (2019). Non-economic factors in violence: Evidence from organized crime, suicides and climate in Mexico. *Journal of Economic Behavior & Organization 168*, 434–452.

Behrer, A. P. and V. Bolotnyy (2022). Heat, crime, and punishment. Policy Research Working Paper 9909, World Bank, Washington, DC.

Bertz, J. W., D. H. Epstein, D. Reamer, W. J. Kowalczyk, K. A. Phillips, A. P. Kennedy, M. L. Jobes, G. Ward, B. A. Plitnick, M. G. Figueiro, et al. (2019). Sleep reductions associated with illicit opioid use and clinic-hour changes during opioid agonist treatment for opioid dependence: Measurement by electronic diary and actigraphy. *Journal of Substance Abuse Treatment 106*, 43–57.

Bobonis, G. J., M. González-Brenes, and R. Castro (2013). Public transfers and domestic violence: The roles of private information and spousal control. *American Economic Journal: Economic Policy 5*(1), 179–205.

Bondurant, S. R., J. M. Lindo, and I. D. Swensen (2018). Substance abuse treatment centers and local crime. *Journal of Urban Economics 104*, 124–133.

BTS (2024). Border Crossing Data. `https://data.bts.gov/Research-and-Statistics/Border-Crossing-Entry-Data/keg4-3bc2/data`. Accessed: 04-09-2024.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Climate and conflict. *Annu. Rev. Econ. 7*(1), 577–617.

Burke, M., M. Zahid, M. C. Martins, C. W. Callahan, R. Lee, T. Avirmed, S. Heft-Neal, M. Kiang, S. M. Hsiang, and D. Lobell (2024). Are we adapting to climate change? NBER Working Papers 32985, National Bureau of Economic Research.

Card, D. and G. B. Dahl (2011). Family violence and football: The effect of unexpected emotional cues on violent behavior. *The Quarterly Journal of Economics 126*(1), 103–143.

Carleton, T., E. Duflo, B. K. Jack, and G. Zappalà (2024). Adaptation to climate change. In *Handbook of the Economics of Climate Change*, Volume 1, pp. 143–248. Elsevier.

Carleton, T. and S. M. Hsiang (2016). Social and economic impacts of climate. *Science 353*(6304), aad9837.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics 137*(4), 2037–2105.

Centers for Disease Control and Prevention (2022). Fast facts: Preventing intimate partner violence. Retrieved from https://www.cdc.gov/violenceprevention/intimatepartnerviolence/fastfact.html. Accessed on 01-15-2024.

Centers for Disease Control and Prevention (2024). Drug overdose surveillance and epidemiology (dose) system: Nonfatal overdose emergency department and inpatient hospitalization discharge data. https://www.cdc.gov/drugoverdose/nonfatal/dose/discharge/dashboard/index.html. Accessed 02-04-2024.

Chang, H. H., H. Zhang, A. D. Latimore, B. P. Murray, R. R. D'Souza, N. Scovronick, M. O. Gribble, and S. T. Ebelt (2023). Associations between short-term ambient temperature exposure and emergency department visits for amphetamine, cocaine, and opioid use in California from 2005 to 2019. *Environment international 181*, 108233.

Christian, C., L. Hensel, and C. Roth (2019). Income Shocks and Suicides: Causal Evidence From Indonesia. *The Review of Economics and Statistics 101*(5), 905–920.

Cicero, T. J. and M. S. Ellis (2015). Abuse-deterrent formulations and the prescription opioid abuse epidemic in the united states: lessons learned from oxycontin. *JAMA psychiatry 72*(5), 424–430.

Cohen, F. and A. Dechezleprêtre (2022). Mortality, temperature, and public health provision: evidence from mexico. *American Economic Journal: Economic Policy 14*(2), 161–192.

Cohen, F. and F. Gonzalez (2024). Understanding the link between temperature and crime. *American Economic Journal: Economic Policy 16*(2), 480–514.

Colmer, J. and J. L. Doleac (2023). Access to guns in the heat of the moment: more restrictive gun laws mitigate the effect of temperature on violence. *Review of Economics and Statistics*, 1–40.

Compton, W. M., R. J. Valentino, and R. L. DuPont (2021). Polysubstance use in the us opioid crisis. *Molecular Psychiatry 26*(1), 41–50.

Dave, D., B. Erten, P. Keskin, and S. Zhang (2025). From addiction to aggression: the spillover effects of opioid policies on intimate partner violence. *Journal of Health Economics*, 103073.

Deiana, C. and L. Giua (2021). The intended and unintended effects of opioid policies on prescription opioids and crime. *The BE Journal of Economic Analysis & Policy 21*(2), 751–792.

Deschênes, O. and M. Greenstone (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review 97*(1), 354–385.

Deza, M., J. C. Maclean, and K. Solomon (2022). Local access to mental healthcare and crime. *Journal of Urban Economics 129*, 103410.

Drug Enforcement Administration (2020). National Drug Threat Assessment (NDTA). https://www.dea.gov/sites/default/files/2021-02/DIR-008-21%202020%20National%20Drug%20Threat%20Assessment_WEB.pdf. Accessed: 04-09-2024.

Erten, B. and P. Keskin (2018). For better or for worse?: Education and the prevalence of domestic violence in Turkey. *American Economic Journal: Applied Economics 10*(1), 64–105.

Erten, B. and P. Keskin (2021). Trade-offs? the impact of wto accession on intimate partner violence in cambodia. *Review of Economics and Statistics*, 1–40.

Esser, M. B., G. P. Guy Jr, K. Zhang, and R. D. Brewer (2019). Binge drinking and prescription opioid misuse in the us, 2012–2014. *American Journal of Preventive Medicine 57*(2), 197–208.

Esser, M. B., C. M. Pickens, G. P. Guy Jr, and M. E. Evans (2021). Binge drinking, other substance use, and concurrent use in the us, 2016–2018. *American Journal of Preventive Medicine 60*(2), 169–178.

Evans, M. F., L. Gazze, and J. Schaller (2025). Temperature and maltreatment of young children. *Review of Economics and Statistics*, 1–37.

Evans, M. F., M. C. Harris, and L. M. Kessler (2022). The hazards of unwinding the prescription opioid epidemic: Implications for child maltreatment. *American Economic Journal: Economic Policy 14*(4), 192–231.

Evans, W. N., E. M. Lieber, and P. Power (2019). How the reformulation of oxycontin ignited the heroin epidemic. *Review of Economics and Statistics 101*(1), 1–15.

Fetzer, T. (2020). Can Workfare Programs Moderate Conflict? Evidence from India. *Journal of the European Economic Association 18*(6), 3337–3375.

Garg, T., M. Jagnani, and V. Taraz (2020). Temperature and Human Capital in India. *Journal of the Association of Environmental and Resource Economists 7*(6), 1113–1150. Publisher: The University of Chicago Press.

Garg, T., G. C. McCord, and A. Montfort (2025). Can social protection reduce damages from higher temperatures? *Journal of Environmental Economics and Management 131*, 103152.

Gihleb, R., O. Giuntella, and N. Zhang (2022). The effect of mandatory-access prescription drug monitoring programs on foster care admissions. *Journal of Human Resources 57*(1), 217–240.

Griffith, K. N., Y. Feyman, S. G. Auty, E. L. Crable, and T. W. Levengood (2021). County-level data on us opioid distributions, demographics, healthcare supply, and healthcare access. *Data in Brief 35*, 106779.

Gros, D. F., M. E. Milanak, K. T. Brady, and S. E. Back (2013). Frequency and severity of comorbid mood and anxiety disorders in prescription opioid dependence. *The American journal on addictions 22*(3), 261–265.

Hahn, R. W., N. Hendren, R. D. Metcalfe, and B. Sprung-Keyser (2025). A welfare analysis of policies impacting climate change. NBER Working Papers 32728, National Bureau of Economic Research.

Heilmann, K., M. E. Kahn, and C. K. Tang (2021). The urban crime and heat gradient in high and low poverty areas. *Journal of Public Economics 197*, 104408.

Hendren, N. and B. Sprung-Keyser (2020). A unified welfare analysis of government policies. *The Quarterly Journal of Economics 135*(3), 1209–1318.

Hensel, M., M. Stuhr, D. Geppert, J. F. Kersten, J. Lorenz, and T. Kerner (2021). Relationship between ambient temperature and severe acute poisoning by alcohol and drugs. *Alcohol 94*, 57–63.

Herrnstein, R. and J. Q. Wilson (1985). Crime and human nature. *New York: Simon and Shuster 9*.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics 8*, 43–75.

Jhang, H., S. Kim, K. Kim, S. Choi, and S.-A. Choe (2025). Extreme ambient temperature and emergency healthcare service utilization due to substance use disorders: a systematic review and meta-analysis. *Scientific Reports 15*(1), 13582.

Kenrick, D. T. and S. W. MacFarlane (1986). Ambient temperature and horn honking: A field study of the heat/aggression relationship. *Environment and Behavior 18*(2), 179–191.

Kirson, N. Y., A. Shei, A. G. White, H. G. Birnbaum, R. Ben-Joseph, L. F. Rossiter, and E. Michna (2014). Societal economic benefits associated with an extended-release opioid with abuse-deterrent technology in the united states. *Pain Medicine 15*(9), 1450–1454.

Kumar, V. M., F. Agboola, P. G. Synnott, C. Segel, M. Webb, D. A. Ollendorf, R. Banken, and R. H. Chapman (2019). Impact of abuse deterrent formulations of opioids in patients with chronic pain in the united states: a cost-effectiveness model. *Value in Health 22*(4), 416–422.

Kuntsche, E. and F. Labhart (2012). Investigating the drinking patterns of young people over the course of the evening at weekends. *Drug and alcohol dependence 124*(3), 319–324.

Luca, D. L., E. Owens, and G. Sharma (2015). Can alcohol prohibition reduce violence against women? *American Economic Review 105*(5), 625–629.

Macours, K., P. Premand, and R. Vakis (2022). Transfers, diversification and household risk strategies: Can productive safety nets help households manage climatic variability? *The Economic Journal 132*(647), 2438–2470.

Martins, S. S., M. C. Fenton, K. M. Keyes, C. Blanco, H. Zhu, and C. L. Storr (2012). Mood and anxiety disorders and their association with non-medical prescription opioid use and prescription opioid-use disorder: longitudinal evidence from the national epidemiologic study on alcohol and related conditions. *Psychological medicine 42*(6), 1261–1272.

McCollister, K. E., M. T. French, and H. Fang (2010). The cost of crime to society: New crime-specific estimates for policy and program evaluation. *Drug and alcohol dependence 108*(1-2), 98–109.

Miczek, K. A., E. W. Fish, R. M. De Almeida, S. Faccidomo, and J. F. Debold (2004). Role of alcohol consumption in escalation to violence. *Annals of the New York Academy of Sciences 1036*(1), 278–289.

Minor, K., A. Bjerre-Nielsen, S. S. Jonasdottir, S. Lehmann, and N. Obradovich (2022). Rising temperatures erode human sleep globally. *One Earth 5*(5), 534–549.

Mitchell, O., D. B. Wilson, and D. L. MacKenzie (2012). The effectiveness of incarceration-based drug treatment on criminal behavior: A systematic review. *Campbell systematic reviews 8*(1), i–76.

Mukherjee, A. and N. J. Sanders (2021). The causal effect of heat on violence: Social implications of unmitigated heat among the incarcerated. NBER Working Papers 28987, National Bureau of Economic Research.

Mullins, J. T. and C. White (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of health economics 68*, 102240.

Mullins, J. T. and C. White (2020). Can access to health care mitigate the effects of temperature on mortality? *Journal of Public Economics 191*, 104259.

Muñoz Sabater, J. (2019). ERA5-Land hourly data on single levels from 1950 to present. Accessed: 11-17-2023.

National Coalition Against Domestic Violence (2020). Domestic violence. Retrieved from https://assets.speakcdn.com/assets/2497/domestic_violence-2020080709350855.pdf?1596811079991. Accessed on 01-15-2024.

Obradovich, N., R. Migliorini, S. C. Mednick, and J. H. Fowler (2017). Nighttime temperature and human sleep loss in a changing climate. *Science Advances 3*(5), e1601555.

Parks, R. M., S. T. Rowland, V. Do, A. K. Boehme, F. Dominici, C. L. Hart, and M.-A. Kioumourtzoglou (2023). The association between temperature and alcohol-and substance-related disorder hospital visits in New York State. *Communications Medicine 3*(1), 118.

Pergolizzi Jr, J. V., R. B. Raffa, and M. H. Rosenblatt (2020). Opioid withdrawal symptoms, a consequence of chronic opioid use and opioid use disorder: Current understanding and approaches to management. *Journal of Clinical Pharmacy and Therapeutics 45*(5), 892–903.

Peterson, C., M. C. Kearns, W. L. McIntosh, L. F. Estefan, C. Nicolaidis, K. E. McCollister, A. Gordon, and C. Florence (2018). Lifetime economic burden of intimate partner violence among US adults. *American Journal of Preventive Medicine 55*(4), 433–444.

Powell, D. and R. L. Pacula (2021). The evolving consequences of oxycontin reformulation on drug overdoses. *American Journal of Health Economics 7*(1), 41–67.

Powell, D., R. L. Pacula, and M. Jacobson (2018). Do medical marijuana laws reduce addictions and deaths related to pain killers? *Journal of Health Economics 58*, 29–42.

Premand, P. and Q. Stoeffler (2022). Cash transfers, climatic shocks and resilience in the sahel. *Journal of Environmental Economics and Management 116*, 102744.

Prendergast, M. L., D. Podus, E. Chang, and D. Urada (2017). The effectiveness of drug abuse treatment: a meta-analysis of comparison group studies. In *Drug Abuse: Prevention and Treatment*, pp. 279–298. Routledge.

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management 67*(3), 274–302.

Rauer, A. J. and M. El-Sheikh (2012). Reciprocal pathways between intimate partner violence and sleep in men and women. *Journal of Family Psychology 26*(3), 470.

Sabia, J. J., D. Dave, F. Alotaibi, and D. I. Rees (2024). The effects of recreational marijuana laws on drug use and crime. *Journal of Public Economics 234*, 105075.

SAMHSA (2018, July). Treatment episode data set (teds): 2015. discharges from substance use treatment services: Tables. Technical report, Center for Behavioral Health Statistics and Quality, U.S. Department of Health and Human Services.

Sarmiento, L., M. Gilli, F. Pavanello, and S. Shayegh (2024). Income shocks, adaptation, and temperature-related mortality: Evidence from the mexican labor market. *CESifo Working Paper Series*.

Seirup, L. and G. Yetman (2006). U.s. census grids (summary file 1), 2000. https://doi.org/10.7927/H4B85623. Accessed 11-17-2023.

Sessler, N. E., J. M. Downing, H. Kale, H. D. Chilcoat, T. F. Baumgartner, and P. M. Coplan (2014). Reductions in reported deaths following the introduction of extended-release oxycodone (oxycontin) with an abuse-deterrent formulation. *Pharmacoepidemiology and drug safety 23*(12), 1238–1246.

Sim, Y. (2023). The effect of opioids on crime: Evidence from the introduction of oxycontin. *International Review of Law and Economics 74*, 106136.

Spiller, H., J. Bailey, R. C. Dart, and S. S. Spiller (2010). Investigation of temporal changes of abuse and misuse of prescription opioids. *Journal of Addictive Diseases 29*(1), 78–83.

Stevenson, B. and J. Wolfers (2006). Bargaining in the shadow of the law: Divorce laws and family distress. *The Quarterly Journal of Economics 121*(1), 267–288.

Studer, J., S. Baggio, M. Mohler-Kuo, P. Dermota, J.-B. Daeppen, and G. Gmel (2014). Differential association of drinking motives with alcohol use on weekdays and weekends. *Psychology of Addictive Behaviors 28*(3), 651.

Swensen, I. D. (2015). Substance-abuse treatment and mortality. *Journal of Public Economics 122*, 13–30.

Tur-Prats, A. (2019). Family types and intimate partner violence: A historical perspective. *Review of Economics and Statistics 101*(5), 878–891.

Tur-Prats, A. (2021). Unemployment and intimate partner violence: A cultural approach. *Journal of Economic Behavior & Organization 185*, 27–49.

Voas, R. B., J. H. Lacey, K. Jones, M. Scherer, and R. Compton (2013). Drinking drivers and drug use on weekend nights in the united states. *Drug and alcohol dependence 130*(1-3), 215–221.

Volkow, N. D. et al. (2014). America's addiction to opioids: Heroin and prescription drug abuse. *Senate Caucus on International Narcotics Control 14*, 1–16.

Yan, E. and D. J. Kuo (2019). I just need an opiate refill to get me through the weekend. *Journal of Medical Ethics 45*(4), 219–224.

Online Appendix "Co-benefits of Substance Abuse Regulation on Temperature and Violent Crime"

Filippo Pavanello, Guglielmo Zappalà

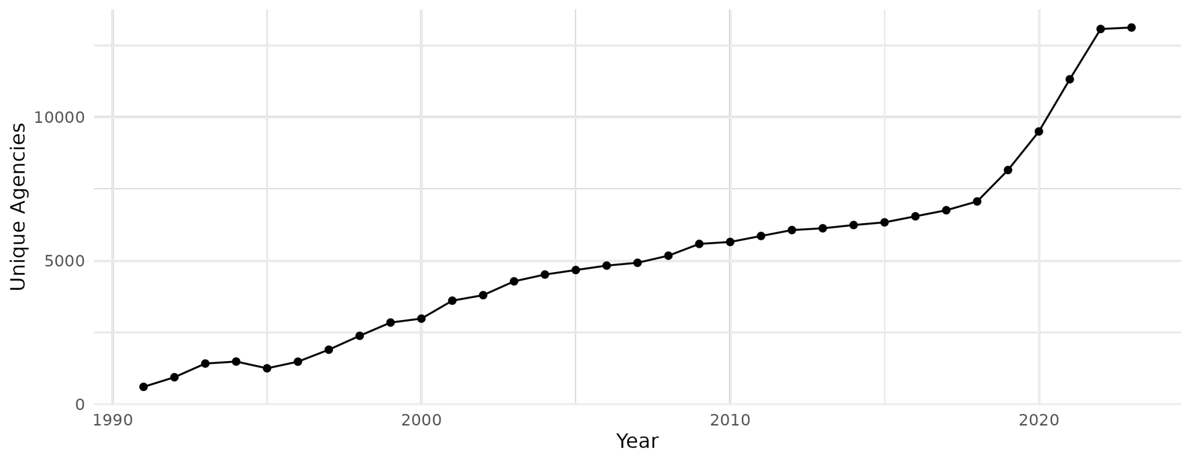
A Descriptive tables and figures

Table A1: Descriptive statistics

	1991-2023		1999-2017		2006-2009		2010-2023	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Daily crimes per 100,000 people								
Total crimes	0.6625	4.2612	0.7084	4.6017	1.3701	6.4213	0.5164	3.5772
Violent crimes	0.1532	1.2498	0.1575	1.3146	0.3055	1.8423	0.1220	1.0614
Assault	0.1474	1.2170	0.1518	1.2817	0.2950	1.7982	0.1171	1.0313
Rape	0.0053	0.1602	0.0053	0.1656	0.0097	0.2212	0.0045	0.1423
Homicide	0.0006	0.0432	0.0005	0.0413	0.0009	0.0537	0.0005	0.0389
Intimate Partner Violence	0.0383	0.4744	0.0409	0.5052	0.0773	0.6895	0.0296	0.3968
Monetary crimes	0.3564	2.5799	0.3862	2.8102	0.7331	3.7546	0.2764	2.1954
Robbery	0.0096	0.1697	0.0105	0.1857	0.0229	0.2709	0.0074	0.1389
Motor Vehicle	0.0314	0.3931	0.0291	0.3854	0.0571	0.5331	0.0255	0.3409
Burglary	0.0600	0.6731	0.0725	0.7597	0.1449	1.0811	0.0426	0.5342
Larceny	0.2226	1.8204	0.2407	1.9920	0.4457	2.5074	0.1708	1.5663
Gambling	0.0001	0.0230	0.0001	0.0251	0.0003	0.0325	0.0001	0.0174
Fraud	0.0327	0.4728	0.0334	0.5038	0.0622	0.6947	0.0302	0.4390
Weather variables								
Average daily temperature (°C)	13.3505	10.1256	11.0319	10.4935	9.6486	9.9349	14.2389	9.9132
Total daily precipitation (m)	0.0029	0.0069	0.0030	0.0069	0.0034	0.0077	0.0028	0.0068
Policies								
Substance abuse treatment facilities (per 100,000 people)			5.390	4.114				
Opioid prescriptions (per capita)					0.67	0.12		
Observations	51,109,015		29,547,742		6,289,662		33,364,097	

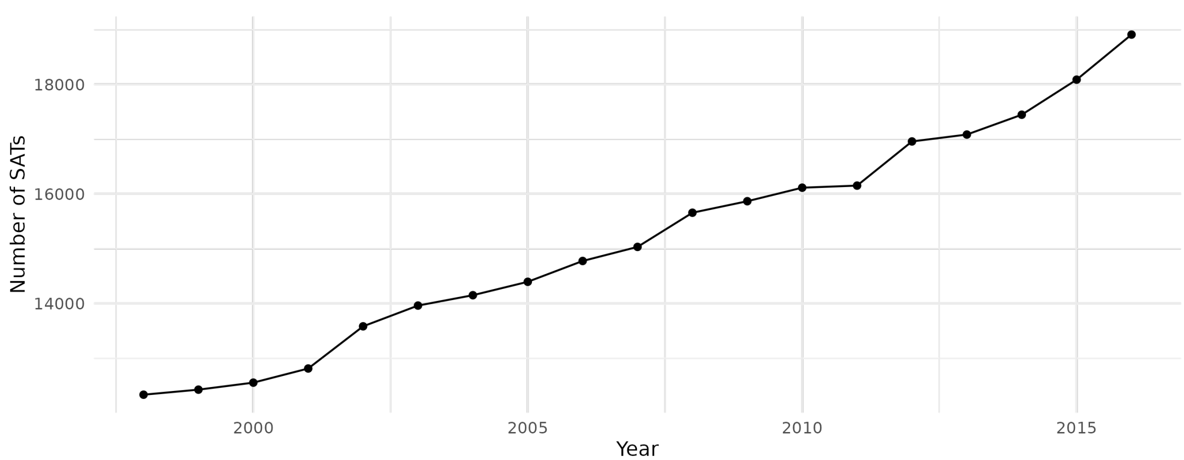
Notes: Daily crime descriptive statistics are weighted by jurisdiction-location population. Substance abuse treatment facilities descriptive statistics refer to the period 1998-2016 and are weighted by county population.

Figure A1: Number of reporting jurisdictions, 1991-2023



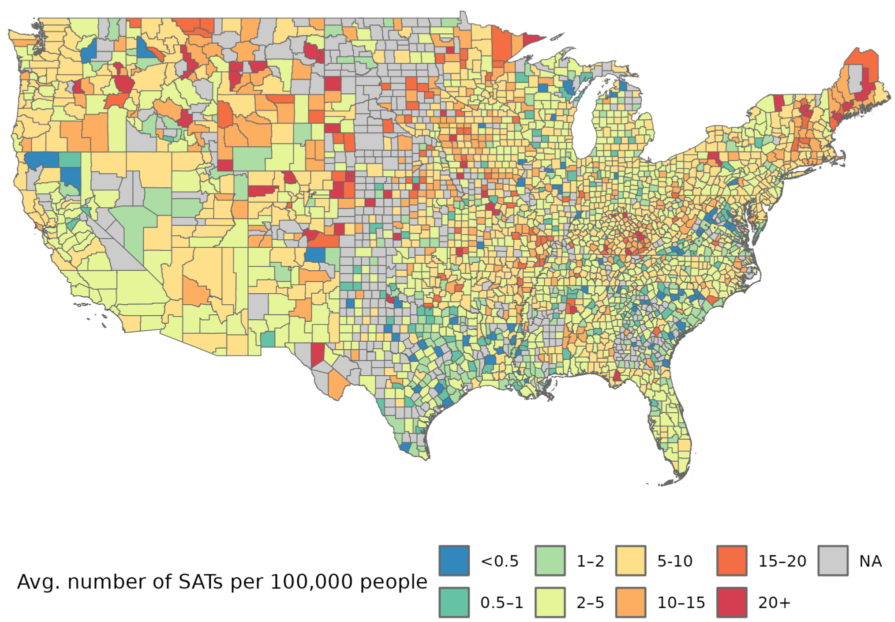
Notes: Figure shows the number of reporting agencies (ORIs) in the NIBRS data set by year.

Figure A2: Number of substance abuse treatment facilities, 1998-2016



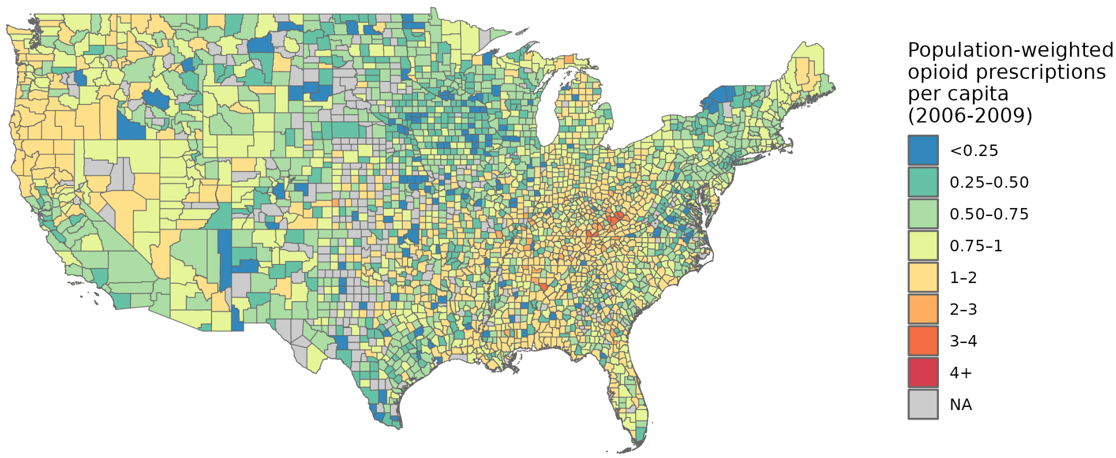
Notes: Figure shows the number of opened substance abuse treatment facilities in the CBS data set by year.

Figure A3: Substance abuse treatment facilities distribution, 1998-2016



Notes: Figure shows the average number of opened substance abuse treatment facilities per 100,000 people between 1998 and 2016 in the CBP data set. Sample mean is 6.14, standard deviation is 5.21.

Figure A4: Pre-reformulation opioid exposure, 2006-2009



Notes: Figure shows the population-weighted average number of opioids prescriptions per capita in the pre-reformulation period from 2006 to 2009 for 2,452 counties in the CDC data set. Sample mean is 0.85, standard deviation is 0.46.

B Temperatures and intimate partner violence

In the U.S., intimate partner violence (IPV) is a widespread and major public health issue. According to the National Coalition Against Domestic Violence (2020), more than 10 million adults experience domestic violence annually. The incidence of this phenomenon is strongly gendered: 1 in 4 women and 1 in 10 men experience sexual violence, physical violence and/or stalking by an intimate partner during their lifetime, and IPV alone accounts for 18% of all violent crime. The consequences of such experiences can be devastating with the estimated lifetime economic cost associated with IPV equal to $3.6 trillion, as a result of medical services for IPV-related injuries, lost productivity from paid work, criminal justice and other costs (Centers for Disease Control and Prevention, 2022).

Prior work has studied economic shocks or policies that may impact women's bargaining power by documenting the effects of emotional cues (Card and Dahl, 2011), cash transfers (Bobonis et al., 2013; Angelucci and Heath, 2020), family structures (Tur-Prats, 2019), labor market shocks, including gender wage gaps (Aizer, 2010) and unemployment (Anderberg et al., 2016; Tur-Prats, 2021), education (Erten and Keskin, 2018), divorce laws (Stevenson and Wolfers, 2006), and trade shocks (Erten and Keskin, 2021). Dave et al. (2025) document that the Oxycontin opioid reformulation significantly reduced intimate partner violence, but induced a notable uptick in heroin-involved intimate partner violence. While an extensive body of research has established a link between higher temperature and violent behavior in the U.S. through physiological and psychological mechanisms, including criminal activity (Ranson, 2014; Heilmann et al., 2021), homicides (Colmer and Doleac, 2023), and child maltreatment (Evans et al., 2025), this paper provides the first evidence of the effect of daily temperatures on intimate partner violence in the United States.

C Temperature and crime

We model the baseline relationship between temperature and crime as follows:

$$Y_{idmy} = f(T_{c(i)dmy}, P_{c(i)dmy}) + \mu_{imt} + \lambda_{wt} + \phi_{dt} + \kappa_{dw} + \varepsilon_{idmy} \tag{C.1}$$

where Y_{idmy} is the number of reported cases of crime per 100,000 people by jurisdiction i in day d of month m and year y; μ_{imt} are jurisdiction-month-year fixed effects; λ_{wt}, ϕ_{dt} and δ_{dw} are respectively week-of-year, day-of-year (calendar day) and day-of-week fixed effects. We cluster standard errors at the county-level and estimate Equation C.1 with population weights at the jurisdiction level. The term $f(T_{c(i)dmy}, P_{c(i)dmy})$ is a function of average daily temperature (in °C) and daily precipitation (in m). In the baseline specification, we linearly model the two weather variables, such that

$$f(T_{c(i)dmy}, P_{c(i)dmy}) = \beta_1 T_{c(i)dmy} + \beta_2 P_{c(i)dmy}$$

The coefficients β_1 and β_2 capture the linear impact of temperature and precipitation exploiting plausibly exogenous quasi-random variation in daily weather realizations (Deschênes and Greenstone, 2007).

We conduct several robustness checks to test our relationship. This includes accounting for COVID19 (Table C3); excluding agencies that do not report for all twelve months (Table C4); alternative fixed-effects, including leveraging interannual rather than intra-month-year variation (Table C5); clustering standard errors at the state level (Table C6); estimating without survey weights (Table C7), and expressing the dependent variable as a count rather than a rate, and using PPML (Table C8).

We also explore non-linear relationship between temperature and crime using polynomials of the weather variables up to the fourth degree (Table C9 and Figure C2),[18] temperature bins (Table C9 and Figure C2), and the share of hours in a day in a temperature bin (Table C11). The estimates suggest that a linear specification is a good approximation of the temperature-crime gradient.

[18] We compute non-linear transformations in temperature and precipitation at the grid-cell level before weighing and averaging, in order to preserve non-linearities in the original weather data (Hsiang, 2016).

In Table C1 we also report the coefficients on precipitation, which is negative correlated with crime rates. We estimate that one-meter increase in daily total precipitation is associated with 0.17 less crime incidents per 100,000. Notably, these results hold only for violent crimes, especially assault, while precipitation is not significantly correlated with monetary crimes, suggesting that precipitation might alter time use behavior and thus reduce crimes involving social interactions.

Finally, Table C12 displays the effects of temperature and precipitation on other monetary crimes. We find a positive association between temperature and property crimes like robbery, motor vehicle, burglary, larceny, and gambling. Notably, similarly to fraud, we do not find a significant coefficient for gambling, another crime that do not involve a physical interaction between offenders and victims.

Table C1: The relationship between temperature and crime (1991-2023)

	Daily crimes per 100,000 people							
	Crime	Violent	Assault	Rape	Homicide	IPV female	Monetary	Fraud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature (°C)	0.0047***	0.0015***	0.0015***	0.000023**	0.000006***	0.0003***	0.0020***	0.000046*
	(0.0016)	(0.0005)	(0.0005)	(0.000009)	(0.000002)	(0.0001)	(0.0007)	(0.000027)
Precipitation (m)	-0.1556**	-0.0949***	-0.0925***	-0.0023	-0.0004	-0.0154**	0.0207	-0.0028
	(0.0771)	(0.0317)	(0.0294)	(0.0030)	(0.0003)	(0.0068)	(0.0288)	(0.0087)
Mean Outcome	0.6623	0.1532	0.1474	0.0053	0.0006	0.0383	0.3563	0.0327
Observations	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C2: The relationship between temperature and violent crimes (Climate terciles)

	Violent Crime (1)	Assault (2)	IPV female (3)
Temperature × Cold	0.0012*	0.0012*	0.0003*
	(0.0007)	(0.0007)	(0.0001)
Temperature × Temperate	0.0022***	0.0021***	0.0005***
	(0.0007)	(0.0007)	(0.0002)
Temperature × Hot	0.0016***	0.0016***	0.0004***
	(0.0005)	(0.0004)	(0.0001)
Precipitation × Cold	-0.0867	-0.0863	-0.0185
	(0.0709)	(0.0689)	(0.0149)
Precipitation × Hot	-0.0530*	-0.0543*	-0.0066
	(0.0306)	(0.0300)	(0.0111)
Precipitation × Temperate	-0.1960***	-0.1805***	-0.0217
	(0.0625)	(0.0557)	(0.0190)
Mean Outcome	0.153	0.147	0.038
Observations	51,088,940	51,088,940	51,088,940
Jurisdiction-Month-Year × Climate FE	✓	✓	✓
Day-of-Year FE	✓	✓	✓
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C3: Relationship between temperature and crime (Excluding Covid-19 years)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Panel A. 1991–2019								
Temperature (°C)	0.0061**	0.0019**	0.0019**	0.00003	0.000006*	0.0004*	0.0026*	0.000068
	(0.0031)	(0.0010)	(0.0009)	(0.00002)	(0.000003)	(0.0002)	(0.0013)	(0.00005)
Precipitation (m)	-0.2185*	-0.1129**	-0.1161**	0.0030	0.0000069	-0.0123	0.0042	-0.0047
	(0.1266)	(0.0516)	(0.0537)	(0.0029)	(0.0004)	(0.0089)	(0.0375)	(0.0107)
Mean Outcome	0.8718	0.1948	0.1876	0.0067	0.0006	0.0506	0.4757	0.0402
Observations	37,687,828	37,687,828	37,687,828	37,687,828	37,687,828	37,687,828	37,687,828	37,687,828
Panel B. Excluding 2020–2021								
Temperature (°C)	0.0043***	0.0014***	0.0013***	0.00002***	0.000005***	0.0003***	0.0018***	0.00005*
	(0.0015)	(0.0005)	(0.0004)	(0.000009)	(0.000002)	(0.0001)	(0.0006)	(0.000025)
Precipitation (m)	-0.1460**	-0.0856***	-0.0834***	-0.0023	-0.00020	-0.0153**	0.0131	-0.0032
	(0.0687)	(0.0288)	(0.0268)	(0.0026)	(0.0003)	(0.0065)	(0.0263)	(0.0078)
Mean Outcome	0.5848	0.1338	0.1288	0.0046	0.0005	0.0336	0.3165	0.0279
Observations	44,607,863	44,607,863	44,607,863	44,607,863	44,607,863	44,607,863	44,607,863	44,607,863
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Panel A estimates the regression in a sample from 2000 to 2019. Panel B uses a sample from 1991 to 2019 and 2022-2023 (excluding years 2020 and 2021). Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors clustered at the county level. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table C4: The relationship between temperature and crime (12-month reporting agencies)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Temperature (°C)	0.0076**	0.0025**	0.0024**	0.00003**	0.000009**	0.0005**	0.0032**	0.000065*
	(0.0034)	(0.0011)	(0.0011)	(0.000015)	(0.000005)	(0.0003)	(0.0014)	(0.00004)
Precipitation (m)	-0.1473	-0.1473**	-0.1443**	-0.0028	-0.0007	-0.0289**	0.1101	0.0093
	(0.0997)	(0.0635)	(0.0590)	(0.0060)	(0.0006)	(0.0147)	(0.0731)	(0.0111)
Mean Outcome	1.0387	0.2400	0.2309	0.0084	0.0009	0.0601	0.5591	0.0515
Observations	43,818,028	43,818,028	43,818,028	43,818,028	43,818,028	43,818,028	43,818,028	43,818,028
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Sample is restricted to agencies reporting crimes for 12 months. Standard errors are clustered at the state level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C5: Relationship between temperature and crime (Alternative fixed effects)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Panel A. State × month-year FE + day-of-year, week-of-year, and day-of-week FE								
Temperature (°C)	0.0099***	0.0028***	0.0027***	0.00004***	0.00001***	0.0007***	0.0050***	0.0002**
	(0.0032)	(0.0009)	(0.0009)	(0.00002)	(0.000005)	(0.0002)	(0.0016)	(0.00008)
Precipitation (m)	0.0728	-0.0470	-0.0455	-0.0018	0.00003	-0.0046	0.1943*	-0.0062
	(0.1257)	(0.0311)	(0.0298)	(0.0030)	(0.0003)	(0.0101)	(0.1032)	(0.0105)
Panel B. Jurisdiction FE + day-of-year, week-of-year, and day-of-week FE								
Temperature (°C)	0.0047**	0.0014**	0.0014**	0.00003**	0.000006**	0.0003**	0.0019*	0.00009***
	(0.0022)	(0.0006)	(0.0006)	(0.00002)	(0.000003)	(0.0001)	(0.0010)	(0.00004)
Precipitation (m)	0.0521	-0.0594*	-0.0588*	-0.0008	0.000003	-0.0120	0.1654	-0.0025
	(0.1467)	(0.0324)	(0.0319)	(0.0024)	(0.0003)	(0.0075)	(0.1249)	(0.0085)
Panel C. Jurisdiction × day-of-year FE and Jurisdiction × month-year FE + date FE								
Temperature (°C)	0.0478***	0.0152***	0.0148***	0.0004***	0.00004***	0.0035***	0.0200***	0.0007***
	(0.0077)	(0.0025)	(0.0024)	(0.00007)	(0.00001)	(0.0006)	(0.0032)	(0.0001)
Precipitation (m)	0.3526	-0.3958**	-0.3954**	0.0009	-0.0020	-0.0720*	0.9818***	0.0648*
	(0.2762)	(0.1674)	(0.1653)	(0.0095)	(0.0027)	(0.0424)	(0.1825)	(0.0331)
Mean Outcome	0.6623	0.1532	0.1474	0.0053	0.0006	0.0383	0.3563	0.0327
Observations	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Panel A includes state×month-year fixed effects and day-of-year, week-of-year, and day-of-week fixed effects. Panel B includes jurisdiction fixed effects and day-of-year, week-of-year, and day-of-week fixed effects. Panel C includes jurisdiction×day-of-year fixed effects plus week-of-year and day-of-week fixed effects. Panel D includes jurisdiction×day-of-year and jurisdiction×month-year fixed effects, as well as date fixed effects. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors clustered at the county level. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table C6: The relationship between temperature and crime (State-level standard errors)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Temperature (°C)	0.0047**	0.0015**	0.0015**	0.000024*	0.000006**	0.0003**	0.0020**	0.000046
	(0.0018)	(0.0006)	(0.0006)	(0.000013)	(0.000002)	(0.0001)	(0.0008)	(0.000040)
Precipitation (m)	-0.1556*	-0.0949***	-0.0925***	-0.0023	-0.0004*	-0.0154**	0.0206	-0.0028
	(0.0828)	(0.0353)	(0.0341)	(0.0037)	(0.0002)	(0.0072)	(0.0404)	(0.0102)
Mean Outcome	0.6625	0.1532	0.1474	0.0053	0.0006	0.0383	0.3564	0.0327
Observations	51,109,015	51,109,015	51,109,015	51,109,015	51,109,015	51,109,015	51,109,015	51,109,015
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors are clustered at the state level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C7: The relationship between temperature and crime (Unweighted)

	Crime	Violent	Assault	Rape	Homicide	IPV female	Monetary	Fraud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature (°C)	0.0863***	0.0248***	0.0242***	0.0005***	0.00007***	0.0056***	0.0327***	0.0012***
	(0.0022)	(0.0010)	(0.0010)	(0.00007)	(0.00002)	(0.0002)	(0.0013)	(0.0003)
Precipitation (m)	-2.035	-1.220***	-1.125**	-0.0856**	-0.0131	-0.0141	0.8285	-0.0922
	(2.059)	(0.4468)	(0.4586)	(0.0396)	(0.0111)	(0.1858)	(1.682)	(0.1394)
Observations	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940
Mean Outcome	12.9210	2.7169	2.6182	0.0929	0.0071	0.6599	6.8641	0.55896
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C8: The relationship between temperature and crime (Count dependent variable)

	Crime	Violent	Assault	Rape	Homicide	IPV female	Monetary	Fraud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. OLS (Count)								
Temperature (°C)	0.0099***	0.0032**	0.0032**	0.0001***	-0.00003	0.0008***	0.0047***	0.0003**
	(0.0032)	(0.0013)	(0.0013)	(0.000035)	(0.00006)	(0.0002)	(0.0011)	(0.0001)
Precipitation (m)	-0.0773	-0.3784	-0.4170*	0.0410	-0.0036	-0.0480	0.1062	0.0462
	(0.6782)	(0.2506)	(0.2398)	(0.0274)	(0.0037)	(0.0331)	(0.1516)	(0.0793)
Mean outcome	1.8279	0.4602	0.4450	0.0132	0.0024	0.0995	0.9459	0.0702
Observations	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940
Panel B. PPML, state-month-year FE								
Temperature (°C)	0.0283***	0.0367***	0.0371***	0.0314***	0.0186**	0.0403***	0.0268***	0.0168***
	(0.0045)	(0.0057)	(0.0058)	(0.0047)	(0.0088)	(0.0057)	(0.0044)	(0.0043)
Precipitation (m)	2.098**	1.725	1.696	3.628*	1.699	2.276*	2.344**	1.404
	(1.017)	(1.211)	(1.234)	(1.894)	(1.510)	(1.306)	(1.095)	(1.192)
Mean outcome	1.8280	0.4602	0.4450	0.0132	0.0025	0.0995	0.9459	0.0702
Observations	51,082,715	51,079,840	51,077,866	51,024,947	48,071,742	51,073,589	51,081,934	51,068,414
Panel C. PPML, jurisdiction-month-year FE								
Temperature (°C)	0.0062***	0.0085***	0.0086***	0.0133***	-0.0030	0.0090***	0.0056***	0.0052**
	(0.0006)	(0.0010)	(0.0010)	(0.0049)	(0.0078)	(0.0014)	(0.0007)	(0.0026)
Precipitation (m)	0.0331	-0.8367**	-0.8885**	1.844	-0.7655	-0.5615**	0.0610	0.3346
	(0.3363)	(0.3966)	(0.4459)	(2.135)	(1.005)	(0.2578)	(0.1789)	(1.043)
Mean outcome	2.5557	1.6956	1.7141	0.1887	0.1297	1.0098	2.1965	0.4720
Observations	46,095,695	39,100,119	38,781,262	12,007,105	1,949,634	27,626,562	42,822,793	23,954,145
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes. Panel A uses OLS regression, Panel B uses Poisson Pseudo-Maximum Likelihood (PPML) with state-month-year fixed effects, and Panel C uses PPML with jurisdiction-month-year fixed effects. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors clustered at the county level. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table C9: The relationship between temperature and crime (Fourth-order polynomial)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Temperature (°C)	0.0066**	0.0013**	0.0013**	0.00003	0.00001**	0.0002**	0.0031**	0.0001*
	(0.0031)	(0.0006)	(0.0006)	(0.00002)	(0.00000)	(0.00010)	(0.0014)	(0.00006)
Temperature^2	-0.00004	0.00003***	0.00003***	0.00000	0.00000	0.00001***	-0.00003	-0.00000
	(0.00006)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00003)	(0.00000)
Temperature^3	-0.000003	-0.0000002	-0.0000002	-0.00000004	-0.000000004	0.00000003	-0.000002	-0.00000010
	(0.000003)	(0.0000006)	(0.000001)	(0.00000004)	(0.000000004)	(0.00000009)	(0.000002)	(0.00000012)
Temperature^4	0.00000005	-0.00000002	-0.00000002	0.00000000	0.00000000003	-0.000000004*	0.00000003	0.000000003
	(0.00000009)	(0.00000002)	(0.00000001)	(0.000000001)	(0.0000000001)	(0.000000002)	(0.00000004)	(0.000000004)
Precipitation (m)	-1.160***	-0.3764***	-0.3607***	-0.0141	-0.0020	-0.0276	-0.2199	-0.0098
	(0.4040)	(0.1325)	(0.1287)	(0.0091)	(0.0019)	(0.0272)	(0.1571)	(0.0389)
Precipitation^2	50.52***	18.76***	17.61**	1.039	0.1060	1.307	7.661	-0.4119
	(18.89)	(7.171)	(6.893)	(0.6466)	(0.1537)	(1.796)	(8.591)	(2.349)
Precipitation^3	-626.4**	-278.7**	-256.1**	-21.10	-1.185	-11.96	-54.57	27.70
	(286.8)	(120.8)	(114.6)	(13.75)	(3.644)	(33.25)	(144.6)	(43.51)
Precipitation^4	1,681.5	907.5*	800.8*	104.0	-1.366	-68.93	11.37	-278.9
	(1,172.6)	(500.4)	(477.8)	(78.97)	(24.77)	(167.8)	(756.7)	(241.5)
Mean Outcome	0.6623	0.1532	0.1474	0.0053	0.0006	0.0383	0.3563	0.0327
Observations	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in meters (m). Regressions are weighted by jurisdiction population. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C10: The relationship between temperature and crime (Bins)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Temperature (°C)								
≤ 5	-0.0686***	-0.0250***	-0.0244***	-0.0005***	-0.00009***	-0.0054***	-0.0272***	-0.0003
	(0.0208)	(0.0074)	(0.0072)	(0.0002)	(0.00003)	(0.0017)	(0.0085)	(0.0004)
5-10	-0.0314***	-0.0149***	-0.0146***	-0.0002**	-0.00006***	-0.0033***	-0.0110***	-0.00009
	(0.0081)	(0.0039)	(0.0038)	(0.0001)	(0.00002)	(0.0009)	(0.0029)	(0.0002)
10-15	-0.0163***	-0.0083***	-0.0081***	-0.0002**	-0.00003**	-0.0020***	-0.0056***	-0.0001
	(0.0043)	(0.0022)	(0.0022)	(0.00007)	(0.00001)	(0.0006)	(0.0015)	(0.0003)
20-25	0.0131***	0.0075***	0.0074***	0.00006	0.00002**	0.0022***	0.0042**	-0.00004
	(0.0044)	(0.0022)	(0.0022)	(0.00004)	(0.00001)	(0.0007)	(0.0019)	(0.0002)
25-30	0.0173***	0.0116***	0.0116***	-0.000008	0.00003**	0.0040***	0.0044**	-0.0005
	(0.0050)	(0.0030)	(0.0030)	(0.00008)	(0.00002)	(0.0010)	(0.0018)	(0.0003)
≥ 30	0.0112***	0.0126***	0.0125***	0.00004	0.00003	0.0047***	-0.0006	-0.0001
	(0.0036)	(0.0033)	(0.0033)	(0.0001)	(0.00002)	(0.0012)	(0.0017)	(0.0005)
Precipitation (m)	-0.4453**	-0.1144**	-0.1146**	0.00005	0.00004	-0.0046	-0.1165	-0.0021
	(0.2032)	(0.0516)	(0.0502)	(0.0039)	(0.0006)	(0.0132)	(0.0870)	(0.0139)
Precipitation^2	5.639*	0.4255	0.5098	-0.0777	-0.0141	-0.2285	2.478	-0.0932
	(3.182)	(1.079)	(0.9567)	(0.1602)	(0.0173)	(0.4297)	(1.724)	(0.3234)
Mean Outcome	0.6623	0.1532	0.1474	0.0053	0.0006	0.0383	0.3563	0.0327
Observations	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Reference category is (15,20] °C. Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C11: The relationship between temperature and crime (Share of hours)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Temperature (°C)								
≤ 5	-0.0748***	-0.0224***	-0.0218***	-0.0006***	-0.00007***	-0.0042***	-0.0323***	-0.0019***
	(0.0213)	(0.0060)	(0.0058)	(0.0002)	(0.00002)	(0.0011)	(0.0094)	(0.0007)
5-10	-0.0130***	-0.0092***	-0.0091***	-0.00005	-0.00003**	-0.0020***	-0.0015	0.00004
	(0.0035)	(0.0018)	(0.0018)	(0.00008)	(0.00001)	(0.0005)	(0.0024)	(0.0004)
10-15	-0.0117***	-0.0060***	-0.0058***	-0.0002**	-0.00002*	-0.0014***	-0.0032***	-0.0004
	(0.0027)	(0.0013)	(0.0012)	(0.00008)	(0.00001)	(0.0004)	(0.0012)	(0.0003)
20-25	0.0052**	0.0063***	0.0063***	-0.00006	0.00003*	0.0024***	0.0006	-0.0017***
	(0.0024)	(0.0017)	(0.0017)	(0.00009)	(0.00001)	(0.0007)	(0.0013)	(0.0005)
25-30	0.0241***	0.0150***	0.0148***	0.0002*	0.00006***	0.0049***	0.0069***	-0.0007
	(0.0055)	(0.0035)	(0.0034)	(0.00009)	(0.00002)	(0.0012)	(0.0020)	(0.0005)
≥ 30	0.0086***	0.0134***	0.0133***	0.00006	0.00006***	0.0047***	-0.0042**	-0.0012**
	(0.0033)	(0.0029)	(0.0029)	(0.00008)	(0.00002)	(0.0010)	(0.0019)	(0.0005)
Precipitation (m)	-0.1977**	-0.0568**	-0.0616***	0.0044	0.0003	0.0055	-0.0082	0.0155
	(0.0770)	(0.0224)	(0.0226)	(0.0030)	(0.0004)	(0.0082)	(0.0433)	(0.0101)
Precipitation^2	1.506	0.1093	0.2471	-0.1288	-0.0114	-0.2027	-0.0411	-0.4619
	(1.682)	(0.5396)	(0.4859)	(0.0956)	(0.0118)	(0.2205)	(1.088)	(0.2919)
Mean Outcome	0.4371	0.1015	0.0976	0.0035	0.0004	0.0253	0.2349	0.0217
Observations	52,189,780	52,189,780	52,189,780	52,189,780	52,189,780	52,189,780	52,189,780	52,189,780
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓

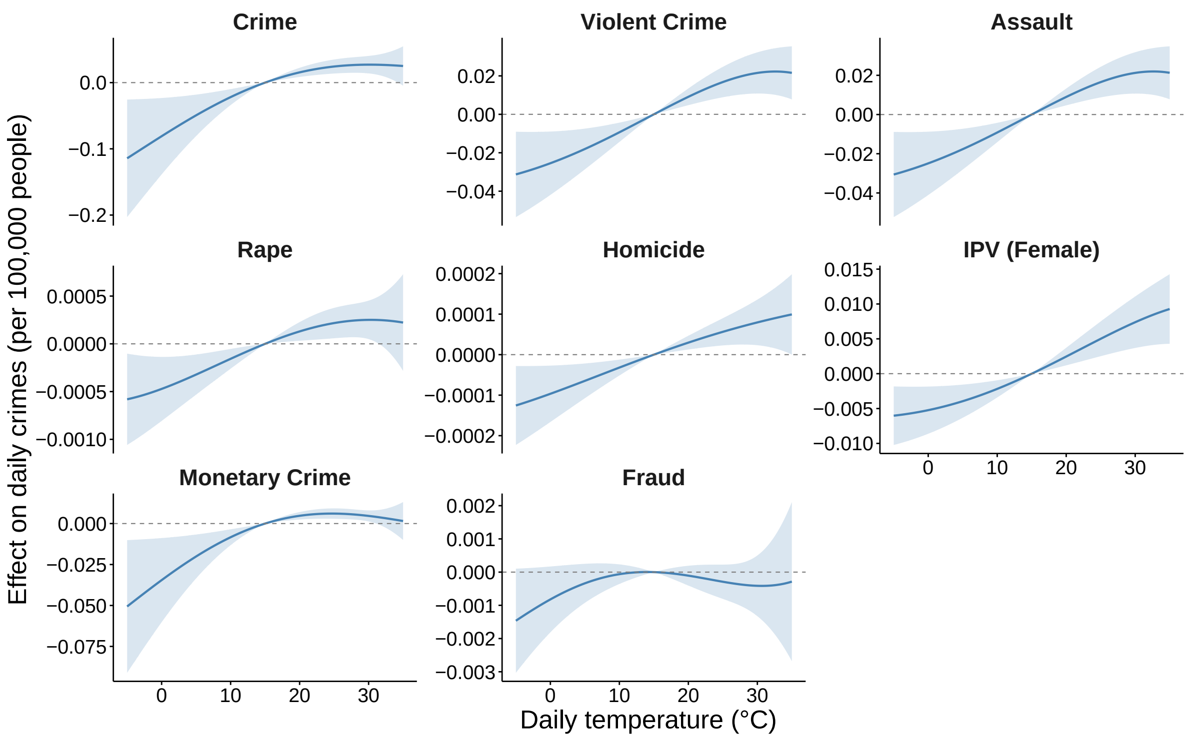
Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is specified as the daily share of hours in each temperature interval. Reference category is (15,20] °C. Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table C12: The relationship between temperature and crime (Other monetary crimes)

	Robbery (1)	Motor Vehicle (2)	Burglary (3)	Larceny (4)	Gambling (5)
Temperature (°C)	0.000075***	0.0001***	0.0005***	0.0012***	0.000000321
	(0.0000266)	(0.0000423)	(0.0002)	(0.0004)	(0.000000341)
Precipitation (m)	0.0001	0.0048	0.0188**	-0.0002	-0.000091
	(0.0016)	(0.0035)	(0.0083)	(0.0183)	(0.0002)
Mean Outcome	0.0096	0.0314	0.0600	0.2226	0.0001
Observations	51,088,940	51,088,940	51,088,940	51,088,940	51,088,940
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓

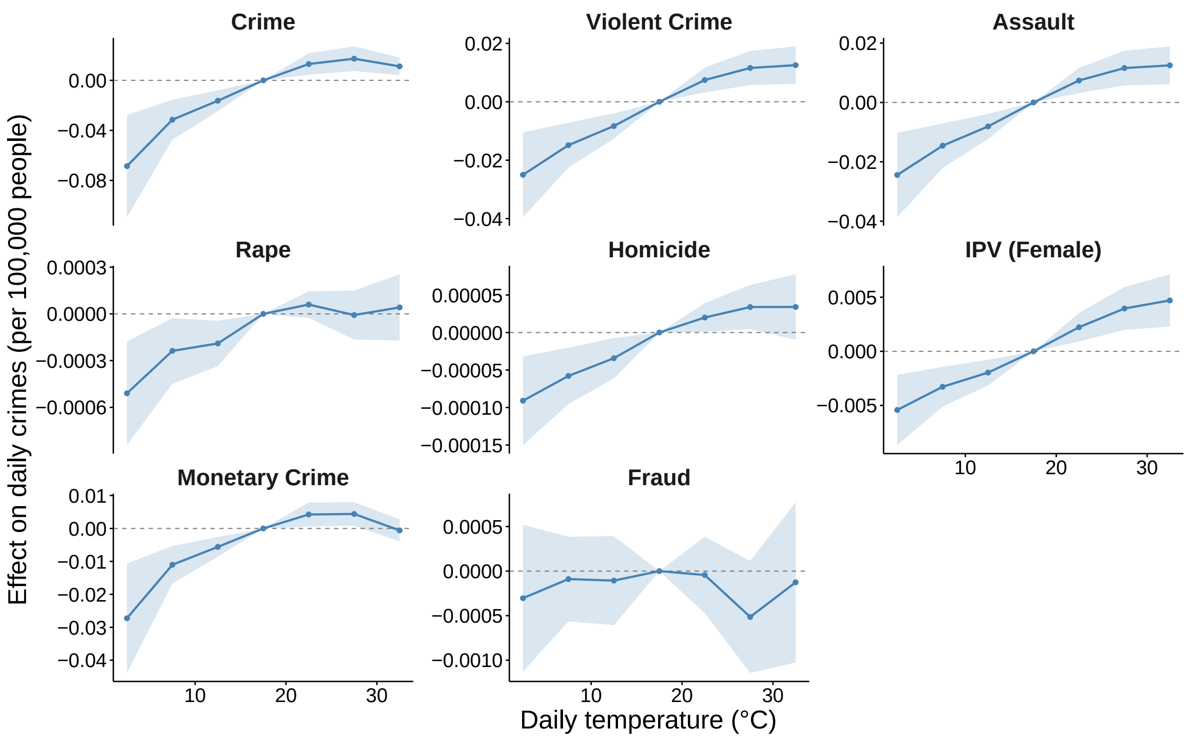
Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Regressions are weighted by jurisdiction population. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Figure C1: The temperature-crime response function (Fourth-order polynomial)



Notes: The figure plots the temperature-crime response functions across different categories of crimes. The response function compare the predicted value of a crime across various temperature levels to its predicted value at 15 °C. The regressions control for daily total precipitation, and jurisdiction-month-year, day-of-year, week-of-year and day-of-week fixed effects. Regressions are weighted by jurisdiction-location population. Confidence intervals at 95% are reported with standard errors clustered at the county-level.

Figure C2: The temperature-crime response function (Bins)



Notes: The figure plots the temperature-crime response functions across different categories of crimes using temperature bins (reference category: (15-20] °C). The regressions control for daily total precipitation, and jurisdiction-month-year, day-of-year, week-of-year and day-of-week fixed effects. Regressions are weighted by jurisdiction-location population. Confidence intervals at 95% are reported with standard errors clustered at the county-level.

D Temperature and substance abuse: Survey evidence

We provide evidence in support of the relationship between temperature and alcohol consumption using individual data from the BRFSS. We estimate the following regression:

$$Y_{idmy} = \beta_1 T^{30d}_{c(i)dmy} + \beta_2 T^{30d}_{c(i)dmy} \times H_{c(i)} + \beta_3 P^{30d}_{c(i)dmy} + \mu_{c(i)} + \phi_{dmy} + \delta_{s(i)m} + \varepsilon_{idmy}$$

where Y_{idmy} is a dummy equal to one if individual i drank heavily in the month before the interview. Heavy drinking is defined based on BRFSS definition: whether in the last month an individual has consumed more than 56 drinks if male, and 28 drinks if female. $T^{30d}_{c(i)dmy}$ and $P^{30d}_{c(i)dmy}$ are the 30-day mean of daily average and the 30-day sum of daily total precipitation prior to the interview date; and $H_{c(i)}$ is a binary indicator equal to one if a county is above 75$^{\text{th}}$ percentile of the pre-2010 opioid exposure. We also account for county ($\mu_{c(i)}$), calendar date (ϕ_{dmy}), and state-month fixed effects ($\delta_{s(i)m}$). We cluster standard errors at the county level, and we estimate the regression using individual sample weights.

Other than the results presented in Table 1, we also find a positive and significant relationship when we substitute the dependent variable with an indicator for alcohol consumption and with the number of alcoholic drinks in the last month (Table D1). In Table D2 we restrict the sample to the years 2006-2012 to match the analysis period of the Oxycontin reformulation analysis.

Table D1: Impact of temperature on alcohol consumption (Other outcomes)

	Drink (Yes = 1)			# of Drinks		
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (°C)	0.000660***	0.00100***	0.000853**	0.0560***	0.0806***	0.0597**
	(0.000)	(0.000)	(0.000)	(0.015)	(0.028)	(0.027)
Precipitation (m)	-0.0268**	0.00461	0.00145	0.655	2.141	2.589*
	(0.011)	(0.014)	(0.013)	(1.055)	(1.396)	(1.385)
Observations	4,046,249	4,046,249	3,842,234	3,994,304	3,994,304	3,793,862
BRFSS Controls			✓			✓
County FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-Month FE		✓	✓		✓	✓
Sample Weights	✓	✓	✓	✓	✓	✓

Notes: In Columns 1-3 the dependent variable is a dummy variable indicating whether the individual has consumed alcohol in the last month. In Columns 4-6 the dependent variable is the number of alcoholic drinks consumed in the last month. Standard errors are clustered at the county level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table D2: Impact of temperature on alcohol consumption (Period 2006-2012)

	Any Drink (Yes = 1)	# of Drinks	Heavy Drinker (Yes = 1)
	(1)	(2)	(3)
Temperature (°C)	0.000298	0.0512	0.000608**
	(0.000)	(0.036)	(0.000)
Precipitation (m)	0.00981	-1.584	-0.00602
	(0.015)	(1.355)	(0.008)
Observations	2,291,605	2,268,459	2,268,459
BRFSS Controls	✓	✓	✓
County FE	✓	✓	✓
Date FE	✓	✓	✓
State-Month FE	✓	✓	✓
Sample Weights	✓	✓	✓

Notes: The sample is restricted to the period 2006-2012. In Column 1 the dependent variable is a dummy variable indicating whether the individual has consumed alcohol in the last month. In Columns 2 the dependent variable is the number of alcoholic drinks consumed in the last month. In Columns 3 the dependent variable is a dummy variable indicating whether the individual was a heavy drinker in the last month. Heavy drinking indicates whether in the last month an individual has consumed more than 56 drinks if male, and 28 drinks if female. Standard errors are clustered at the county level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table D3: Heterogeneity by opioid exposure: Impact of temperature on alcohol consumption (Other outcomes)

	Any Drink (Yes = 1)	# of Drinks
	(1)	(2)
Temperature (° C)	-0.0000899	0.00128
	(0.001)	(0.052)
Temperature × High (Yes = 1)	0.000461*	0.0120
	(0.000)	(0.028)
Observations	1,250,607	1,228,916
BRFSS Controls	✓	✓
Precipitation Controls	✓	✓
County FE	✓	✓
Date FE	✓	✓
State-Month FE	✓	✓
Sample Weights	✓	✓

Notes: The sample is restricted to the period 2006-2009. In Column 1 the dependent variable is a dummy variable indicating whether the individual has consumed alcohol in the last month. In Columns 2 the dependent variable is the number of alcoholic drinks consumed in the last month. Standard errors are clustered at the county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

E Substance abuse treatment facilities: additional results and robustness

E.1 Alternative specifications

Direct effect of SAT facilities. Our baseline model does not allow us to identify a direct effect of SAT expansion, that is absorbed by jurisdiction-month-year fixed effects. We relax our specification to study the direct effect of opening an additional SAT facility. Our specification is written as follows:

$$
\begin{aligned}
Y_{idmt} = \quad & \alpha\, SAT_{c(i)t-1} + \beta_1\, T_{c(i)dmt} \times SAT_{c(i)t-1} + \beta_2\, T_{c(i)dmt} + \\
& + \gamma_1\, P_{c(i)dmt} \times SAT_{c(i)t-1} + \gamma_2\, P_{c(i)dmt} + \\
& + \mu_{idm} + \lambda_{mt} + \varepsilon_{idmt}
\end{aligned}
\tag{E.1}
$$

Because SAT varies only at the county–year level, the main effect α is identified from the remaining cross-county-year variation, while the interaction terms β_1 and γ_1 exploit within-county, within-year daily variation in temperature and precipitation. We control for national level unobserved shocks through month-year (λ_{mt}) and day-of-week (κ_{dw}) fixed effects.

We report our results in Panel A of Table E2. We estimate that an additional SAT facility per 100,000 residents reduces daily violent crimes by 0.029 incidents per 100,000 people.[19] The magnitude of the estimated coefficients remains similar across categories of violent crimes—assault and intimate partner violence. SAT have a positive effect also on fraud crimes. A plausible explanation is that the establishment of treatment centers often brings inflows of public funding, subsidies, and insurance reimbursements, which may increase incentives for fraudulent behavior or improve detection and reporting of such crimes. Although the interaction coefficient between temperatures and SAT is also statistically significant, its magnitude is small.

We estimate four alternative specifications to test for the robustness of our estimates (Table E2, Panels B–E). Panel B estimates Equation 1 without interacting temperature and precipitation with county and year indicators. While the interaction coefficient is smaller in

[19] This result is aligned with prior work documenting a 0.12–0.34% reduction in monthly violent crimes for an additional SAT (Bondurant et al., 2018).

magnitude relative to the baseline specification (Table E3), it remains negative and statistically significant. This specification allows us to compare the direct effect of temperatures and the mitigating role of SAT facilities. Under this approach, the opening of an additional SAT facility per 100,000 residents offsets approximately 3.7% of temperature-induced violent crimes and assaults, and 3.98% of temperature-induced intimate partner violence incidents. Panel C similarly excludes county- and year-specific weather interactions, but instead exploits within-jurisdiction day-of-year and month-year variation while additionally controlling for date fixed effects; results remain stable. In Panel D, the interaction term on fraud is weakly significant once we reintroduce interactions between weather variables and county and year indicators. Finally, Panel E replaces day-of-week, day-of-year, and week-of-year fixed effects with date fixed effects, with estimates similar to our baseline results.

E.2 Additional figures and tables

Table E1: Temperatures and opioid prescriptions and reformulation do not predict SAT facility opening

	# SAT	# SAT per 100,000s	# SAT	# SAT per 100,000s
	(1)	(2)	(3)	(4)
Temperature	0.4732	-0.0936	0.6571	-0.0217
	(0.5219)	(0.1104)	(0.5550)	(0.1174)
Temperature × Opioid exposure	0.1229	0.0962	-0.0751	-0.0143
	(0.2501)	(0.0636)	(0.3117)	(0.0730)
Temperature × Post 2010			-0.6778	-0.0224
			(0.4586)	(0.0735)
Temperature × Opioid exposure × Post 2010			0.3114	0.0838
			(0.3585)	(0.0519)
Mean Outcome	33.529	5.803	33.529	5.803
Observations	13,000	13,000	13,000	13,000
Precipitation	✓	✓	✓	✓
Precipitation × Opioid exposure	✓	✓	✓	✓
Precipitation × Post 2010			✓	✓
Precipitation × Opioid exposure × Post 2010			✓	✓
County FE	✓	✓	✓	✓
State-Year FE	✓	✓	✓	✓
County Population Weights	✓	✓	✓	✓

Notes: Regressions are at the county-year level over the sample period 2006-2016. The dependent variable is the number of SAT facilities (columns 1, 3) or the number of SAT facilities per 100,000 people (columns 2, 4). Temperature is the average daily temperature measured in degrees Celsius (°C). *Opioid exposure* indicates the average number of opioid prescriptions per capita in the pre-policy period 2006-2009. *Post 2010* is an indicator variable equal to 1 from 2010 onwards. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E2: The mitigating effect of substance-abuse treatment facilities (Alternative fixed effects)

	Daily crimes per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Panel A: Jurisdiction-Day-of-Year + Month-Year + Day-of-Week				
Temperature	0.0131**	0.0126**	0.0029**	0.0011**
	(0.0063)	(0.0061)	(0.0014)	(0.0005)
SAT	-0.0294***	-0.0292***	-0.0088***	0.0197***
	(0.0069)	(0.0068)	(0.0019)	(0.0018
Temperature × SAT	-0.0009**	-0.0009**	-0.0002**	-0.0000931**
	(0.0004)	(0.0003)	(0.000077)	(0.0000405)
Panel B: Jurisdiction-Month-Year + Day-of-Year + Week-of-Year + Day-of-Week				
Temperature	0.0027**	0.0027**	0.0006**	0.0002*
	(0.0009)	(0.0009)	(0.0002)	(8.53e-5)
Temperature × SAT	-0.0001**	-0.0001**	-2.39e-5**	-1.23e-5**
	(0.0000383)	(0.0000373)	(0.00000863)	(0.00000496)
Panel C: Jurisdiction-Day-of-Year + Jurisdiction-Month-Year + Date				
Temperature	0.0429***	0.0418***	0.0100***	0.0017***
	(0.0022)	(0.0022)	(0.0006)	(0.0002)
Temperature × SAT	-0.0029***	-0.0028***	-0.0007***	-0.0001***
	(0.0002)	(0.0002)	(0.0000479)	(0.0000221)
Panel D: Jurisdiction-Day-of-Year + Jurisdiction-Month-Year + Date + Temp/Precip × Year/County				
Temperature × SAT	-0.0006***	-0.0006***	-0.0001***	0.0000625*
	(0.0000927)	(0.0000905)	(0.0000354)	(0.0000371)
Panel E: Jurisdiction-Month-Year + Date + Temp/Precip × Year/County				
Temperature × SAT	-0.0009***	-0.0009***	-0.0002***	-0.0000139
	(0.0001)	(0.0001)	(0.0000425)	(0.0000362)
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	26,879,916	26,879,916	26,879,916	26,879,916

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1999-2017. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E3: The mitigating effect of substance-abuse treatment facilities

	Daily crimes per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT	-0.0008***	-0.0008***	-0.0002***	-0.000036
	(0.0001)	(0.0001)	(0.00004)	(0.00003)
Precipitation × SAT	-0.0820*	-0.0815**	-0.0623***	0.0039
	(0.0423)	(0.0409)	(0.0216)	(0.0206)
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	26,879,916	26,879,916	26,879,916	26,879,916
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1999-2017. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E4: The mitigating effect of substance-abuse treatment facilities (Other crimes)

	Daily crimes per 100,000 people		
	Rape (1)	Homicide (2)	Gambling (3)
Temperature × SAT	0.00000212	-0.00000243	-0.00000213
	(0.0000118)	(0.0000298)	(0.0000148)
Precipitation × SAT	0.0018	-0.0020	-0.0017
	(0.0072)	(0.0022)	(0.0014)
Mean Outcome	0.0144	0.0013	0.0003
Observations	26,879,916	26,879,916	26,879,916
Jurisdiction-Month-Year FE	✓	✓	✓
Day-of-Year FE	✓	✓	✓
Week-of-Year FE	✓	✓	✓
Day-of-Week FE FE	✓	✓	✓
Temperature × County	✓	✓	✓
Temperature × Year	✓	✓	✓
Precipitation × County	✓	✓	✓
Precipitation × Year	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *SAT* indicates whether the number of open SAT per 100,000 people in the previous year. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E5: The mitigating effect of substance-abuse treatment facilities (Including never treated)

	Daily crimes per 100,000 people			
	Violent Crimes (1)	Assault (2)	IPV (3)	Fraud (4)
Temperature × SAT	-0.0008***	-0.0008***	-0.0002***	-0.0000334
	(0.0001)	(0.0001)	(0.0000388)	(0.0000329)
Precipitation × SAT	-0.0838**	-0.0833**	-0.0674***	0.0044
	(0.0412)	(0.0398)	(0.0212)	(0.0200)
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	30,245,622	30,245,622	30,245,622	30,245,622
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1999-2017. The sample includes counties that never have a SAT according to the CBP data set in the sample period. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E6: The mitigating effect of substance-abuse treatment facilities (12-month reporting agencies)

	Daily crimes per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT	-0.0009***	-0.0008***	-0.0002***	-0.00006
	(0.0001)	(0.0001)	(0.0000388)	(0.0000378)
Precipitation × SAT	-0.0515	-0.0514	-0.0483**	-0.0149
	(0.0476)	(0.0456)	(0.0234)	(0.0232)
Mean Outcome	3.232	3.120	0.8680	0.4942
Observations	23,622,231	23,622,231	23,622,231	23,622,231
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1998-2016. The sample includes only jurisdictions that reported for twelve consecutive months to NIBRS. “Mean Outcome“ is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E7: The mitigating effect of substance-abuse treatment facilities (Number of establishments)

	Daily crimes per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT	-0.0003***	-0.0003***	-0.0000635**	-0.00000711
	(0.0001)	(0.0001)	(0.0000256)	(0.0000187)
Precipitation × SAT	-0.0458*	-0.0434*	-0.0395***	-0.0146
	(0.0266)	(0.0261)	(0.0100)	(0.0117)
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	26,879,916	26,879,916	26,879,916	26,879,916
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1997-2016. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E8: The mitigating effect of substance-abuse treatment facilities (First opening)

	Daily crimes per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT (first opening)	-0.0031	-0.0035*	-0.0009	-0.0005
	(0.0021)	(0.0021)	(0.0010)	(0.0016)
Precipitation × SAT (first opening)	-2.702**	-2.815**	-0.8640	-1.496**
	(1.264)	(1.270)	(0.7028)	(0.7481)
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	26,879,916	26,879,916	26,879,916	26,879,916
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the first ever opening of a SAT facility in a county in the previous year. The sample period is 1999-2017. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E9: The mitigating effect of substance-abuse treatment facilities by time of the day

	Time of the day			
	Morning	Afternoon	Evening	Night
	(1)	(2)	(3)	(4)
Panel A: Violent Crimes				
Temperature × SAT	-0.00004*	-0.0002***	-0.0004***	-0.0002***
	(0.00002)	(0.00003)	(0.00007)	(0.00004)
Mean Outcome	0.0641	0.1246	0.1616	0.0824
Panel B: Assault				
Temperature × SAT	-0.00005**	-0.0002***	-0.0004***	-0.0002***
	(0.00002)	(0.00003)	(0.00007)	(0.00004)
Mean Outcome	0.0616	0.1208	0.1577	0.0781
Panel C: Intimate Partner Violence				
Temperature × SAT	-0.00001	-0.00003**	-0.00008***	-0.00005***
	(0.00001)	(0.00001)	(0.00002)	(0.00002)
Mean Outcome	0.0164	0.0270	0.0466	0.0264
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Observations	26,521,081	26,521,081	26,521,081	26,521,081

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average temperature during morning, afternoon, evening and night, measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1999-2017. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E10: The mitigating effect of substance-abuse treatment facilities by day of the week

	Day of the week					
	Violent Crime		Assault		Intimate Partner Violence	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × SAT	-0.0007***	-0.0012***	-0.0008***	-0.0012***	-0.0002***	-0.0003***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0000416)	(0.0000763)
Precipitation × SAT	-0.0396	0.0146	-0.0392	0.0148	-0.0271	0.0061
	(0.0481)	(0.0798)	(0.0461)	(0.0782)	(0.0242)	(0.0402)
Mean Outcome	0.422	0.500	0.407	0.484	0.106	0.152
Observations	19,195,466	7,684,450	19,195,466	7,684,450	19,195,466	7,684,450
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1999-2017. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table E11: Heterogeneous effects of substance-abuse treatment facilities on temperature-violent crime by crime characteristics

	Daily crimes per 100,000 people					
	No Firearm	Firearm	Indoor	Outdoor	Home	Outside
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Violent Crimes						
Temperature × SAT	-0.0006***	-0.0000212*	-0.0005***	-0.0001***	-0.0004***	-0.0003***
	(0.0001)	(0.0000171)	(0.0000855)	(0.0000152)	(0.0000793)	(0.0000636)
Mean Outcome	0.358	0.014	0.347	0.020	0.286	0.128
Panel B: Assault						
Temperature × SAT	-0.0006***	-0.000021*	-0.0005***	-0.0001***	-0.0004***	-0.0003***
	(0.0001)	(0.0000108)	(0.0000834)	(0.0000149)	(0.0000772)	(0.0000623)
Mean Outcome	0.343	0.014	0.334	0.020	0.275	0.125
Panel C: Intimate Partner Violence						
Temperature × SAT	-0.0002***	-0.000000365	-0.0002***	-0.0000045	-0.0002***	-0.00000893
	(0.0000362)	(0.0000029)	(0.0000365)	(0.00000517)	(0.0000357)	(0.0000100)
Mean Outcome	0.104	0.002	0.105	0.003	0.100	0.016
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Temperature × County	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓
Precipitation × County	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓
Observations	26,879,916	26,879,916	26,879,916	26,879,916	26,879,916	26,879,916

Notes: The dependent variable is the number of crimes per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *SAT* indicates the number of open SAT facilities per 100,000 people in the previous year. The sample period is 1999-2017. "Mean Outcome" is the average number of crimes in counties without any SAT establishments during the sample period. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

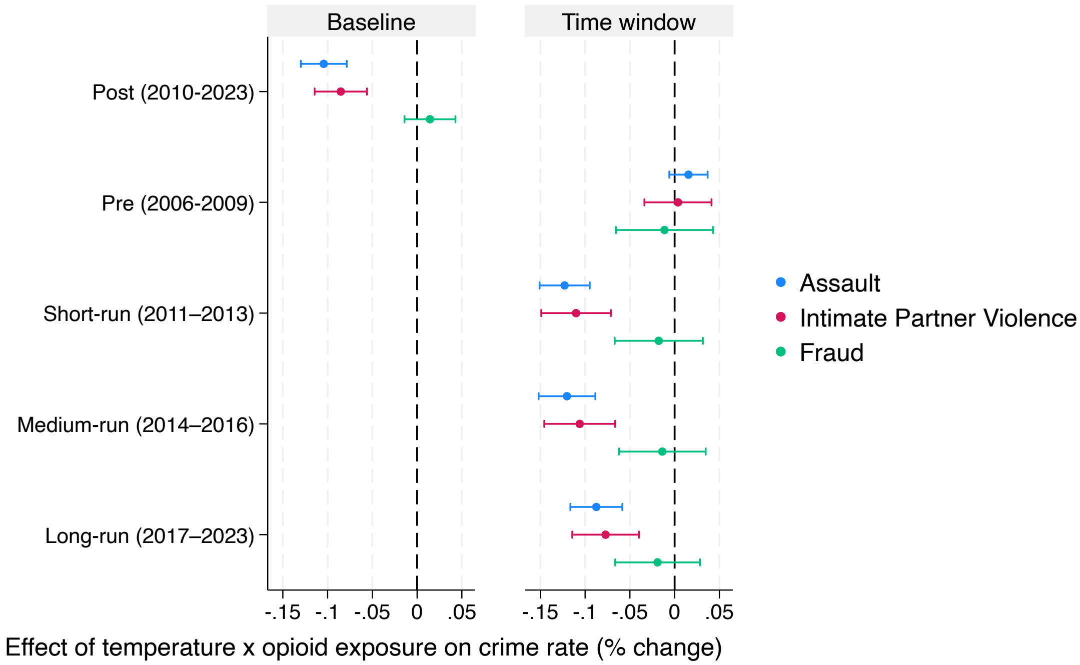
F Opioid reformulation: Additional results and robustness

Table F1: Effects of opioid reformulation on temperature and crimes

	Daily crimes per 100,000 people								
	Violent crimes (1)	Assault (2)	Rape (3)	Homicides (4)	IPV (5)	Monetary crimes (6)	Robbery (7)	Fraud (8)	Gambling (9)
Temperature × Opioid exposure	0.0336***	0.0329***	0.000606**	0.000110*	0.00686***	0.0514***	0.00211***	0.000488	0.0000651
	(0.00420)	(0.00410)	(0.000268)	(0.0000597)	(0.00120)	(0.00587)	(0.000687)	(0.000963)	(0.0000541)
Temperature × Opioid exposure × Post-2010	-0.0341***	-0.0334***	-0.000609**	-0.000113*	-0.00696***	-0.0523***	-0.00218***	-0.000484	-0.0000661
	(0.00414)	(0.00404)	(0.000269)	(0.0000597)	(0.00119)	(0.00581)	(0.000677)	(0.000964)	(0.0000541)
Observations	38,033,629	38,033,629	38,033,629	38,033,629	38,033,629	38,033,629	38,033,629	38,033,629	38,033,629
Pre-policy outcome mean	0.304	0.294	0.0096	0.0009	0.077	0.787	0.030	0.068	0.0003
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓	✓

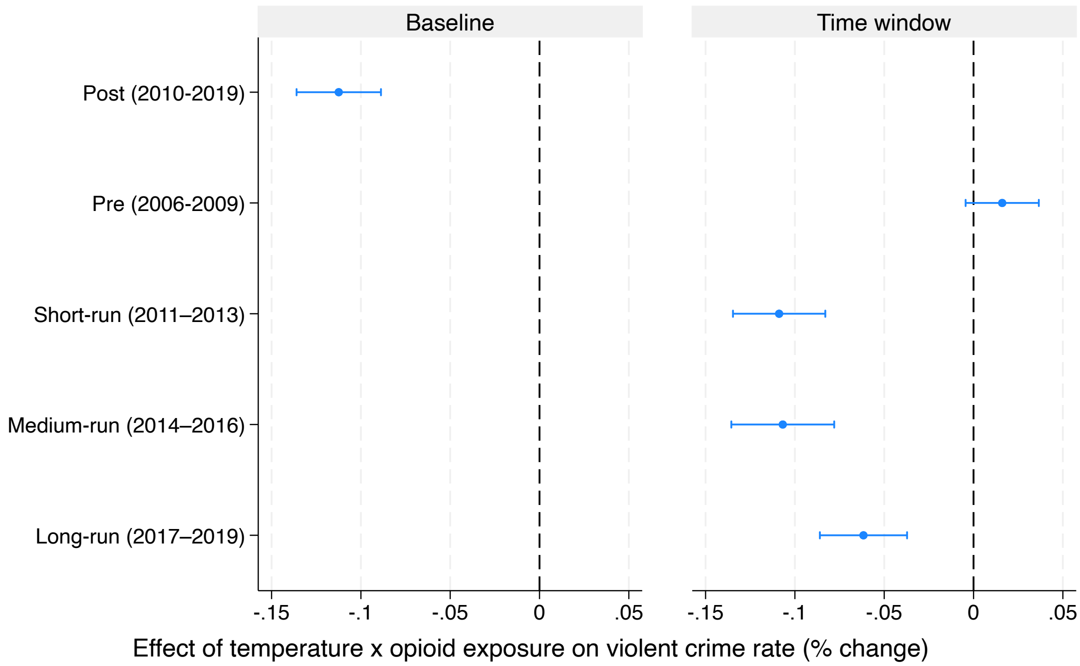
Notes: The dependent variable is the number of crimes per 100,000 people. *Post-2010* is a dummy variable equal to 1 for the post-reformulation period, starting from 2010. *Opioid exposure* is the county-level pre-2010 exposure to opioids. Standard errors are clustered at the county level. All regressions are weighted using jurisdiction population weights. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Figure F1: Differential effects of opioid reformulation on temperature-crimes over time



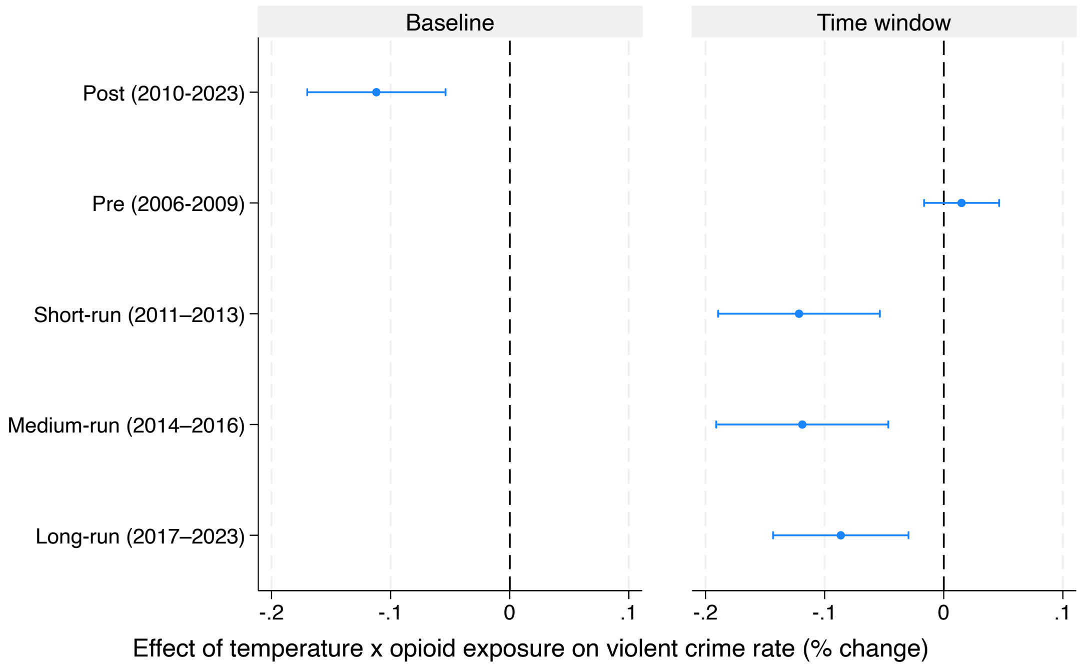
Notes: Each panel and color corresponds to a separate regression. The dependent variable is the daily charge rate per 100,000 inhabitants, normalized on the y-axis according to the average charge rate of each category before 2010. The figure plots the coefficients of the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opioid prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation years, 2010-2019, and in the right graph an indicator variable (short-run) equal to one for the years immediately following reformulation, 2011 to 2013, another one (medium-run) equal to one for the years 2014 to 2016, and another indicator variable (long-run) for the years 2017-2019 on the jurisdiction-level rate of crimes. The regression also controls for year-specific and state-specific temperature and precipitation coefficients, jurisdiction-month-year, week-of-year, day-of-year and day-of-week fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the county-level.

Figure F2: Differential effects of opioid reformulation on temperature-violent crimes over time excluding Covid-19 period



Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opioid prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation years, 2010-2019, and in the right graph an indicator variable (short-run) equal to one for the years immediately following reformulation, 2011 to 2013, another one (medium-run) equal to one for the years 2014 to 2016, and another indicator variable (long-run) for the years 2017-2019 on the jurisdiction-level rate of violent crimes. The regression also controls for year-specific and state-specific temperature and precipitation coefficients, jurisdiction-month-year, week-of-year, day-of-year and day-of-week fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the county-level.

Figure F3: Differential effects of opioid reformulation on temperature-violent crimes clustering standard errors at the state-level)



Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opioid prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation years, 2010-2023, and in the right graph an indicator variable (short-run) equal to one for the years immediately following reformulation, 2011 to 2013, another one (medium-run) equal to one for the years 2014 to 2016, and another indicator variable (long-run) for the years 2017-2023, several years post-reformulation. The regression also controls for year-specific and state-specific temperature and precipitation coefficients, jurisdiction-month-year, week-of-year, day-of-year and day-of-week fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the state-level.

Table F2: Effects of opioid reformulation on temperature and crimes. Aggregating data at different levels.

	Jurisdiction-Month			County-Day		
	Violent Crimes	Assault	IPV	Violent Crimes	Assault	IPV
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × Opioid exposure	1.045***	1.022***	0.161***	0.0382***	0.0378***	0.00679***
	(0.148)	(0.145)	(0.0270)	(0.00529)	(0.00518)	(0.00130)
Temperature × Opioid exposure × Post-2010	-1.139***	-1.112***	-0.181***	-0.0421***	-0.0414***	-0.00759***
	(0.119)	(0.117)	(0.0231)	(0.00447)	(0.00440)	(0.00112)
Jurisdiction-Year FE	✓	✓	✓			
Month-Year FE	✓	✓	✓			
County-Month-Year FE				✓	✓	✓
Week-of-Year FE				✓	✓	✓
Day-of-Week FE				✓	✓	✓
Day-of-Year FE				✓	✓	✓
Temperature-Year				✓	✓	✓
Precipitation-Year				✓	✓	✓
Temperature-State	✓	✓	✓	✓	✓	✓
Precipitation-State	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓
Observations	1,029,168	1,029,168	1,029,168	8,744,657	8,744,657	8,744,657
Pre-policy mean outcome	10.702	10.367	2.349	0.359	0.348	0.079

Notes: The outcome variable is the crime rate aggregated at the jurisdiction-month level (columns 1-3) and at the county-day level (columns 4-6). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F3: Effects of opioid reformulation on temperature and crimes. Seasonal differences.

	Seasonal differences			
	No Winter	No Spring	No Summer	No Fall
	(1)	(2)	(3)	(4)
Panel A: Violent Crimes				
Temperature × Opioid exposure	0.0405***	0.0303***	0.0335***	0.0306***
	(0.00472)	(0.00418)	(0.00445)	(0.00385)
Temperature × Opioid exposure × Post-2010	-0.0411***	-0.0309***	-0.0341***	-0.0311***
	(0.00467)	(0.00413)	(0.00439)	(0.00378)
Pre-policy mean outcome	0.315	0.300	0.298	0.305
Panel B: Assaults				
Temperature × Opioid exposure	0.0390***	0.0297***	0.0330***	0.0303***
	(0.00458)	(0.00405)	(0.00436)	(0.00378)
Temperature × Opioid exposure × Post-2010	-0.0396***	-0.0303***	-0.0335***	-0.0308***
	(0.00454)	(0.00399)	(0.00430)	(0.00371)
Pre-policy mean outcome	0.304	0.290	0.288	0.294
Panel C: Intimate Partner Violence				
Temperature × Opioid exposure	0.00865***	0.00585***	0.00652***	0.00671***
	(0.00146)	(0.00133)	(0.00121)	(0.00113)
Temperature × Opioid exposure × Post-2010	-0.00881***	-0.00593***	-0.00663***	-0.00680***
	(0.00145)	(0.00132)	(0.00119)	(0.00112)
Pre-policy mean outcome	0.079	0.076	0.075	0.078
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Observations	28,638,775	28,452,657	28,452,657	28,556,798

Notes: Each column estimates Equation (2) excluding one season. Winter includes December, January, and February. Spring includes March, April, May. Summer includes June, July, August. Fall includes September, October, November. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F4: Effects of opioid reformulation on temperature and crimes. Alternative measures of opioid exposure.

	Daily crimes per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Panel A: Pills				
Temperature × Opioid exposure	0.000406***	0.000400***	0.0000677**	-0.0000107
	(0.000111)	(0.000109)	(0.0000321)	(0.0000219)
Temperature × Opioid exposure × Post-2010	-0.000417***	-0.000411***	-0.0000698**	0.00000940
	(0.000106)	(0.000105)	(0.0000309)	(0.0000219)
Pre-policy mean opioid exposure	36.14	36.14	36.14	36.14
Panel B: Shipments				
Temperature × Opioid exposure	0.309***	0.302***	0.0630***	0.00354
	(0.0464)	(0.0454)	(0.0133)	(0.0106)
Temperature × Opioid exposure × Post-2010	-0.329***	-0.321***	-0.0665***	-0.00442
	(0.0445)	(0.0435)	(0.0129)	(0.0106)
Pre-policy mean opioid exposure	0.09	0.09	0.09	0.09
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Week fixed effects	✓	✓	✓	✓
Day-of-Year fixed effects	✓	✓	✓	✓
Week-of-Year fixed effects	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Pre-policy mean outcome	0.305	0.295	0.077	0.068
Observations	39,105,573	39,105,573	39,105,573	39,105,573

Notes: *Panel A* uses the average opioid pills and *Panel B* uses the average shipments per capita to measure opioid exposure at the county-level between 2006 and 2009. Data on opioid pill volumes were obtained from the U.S. Drug Enforcement Administration's Automation of Reports and Consolidated Orders System (ARCOS) pill shipment database (Griffith et al., 2021). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F5: Effect of opioid reformulation on temperature-crimes only on jurisdictions with 12 months of consistent reporting

	Cases per 100,000 people			
	Violent Crimes	Assault	Intimate Partner Violence	Fraud
	(1)	(2)	(3)	(4)
Temperature × Opioid exposure	0.0285***	0.0279***	0.00530***	0.000659
	(0.00378)	(0.00369)	(0.00113)	(0.00106)
Temperature × Opioid exposure × Post-2010	-0.0283***	-0.0277***	-0.00526***	-0.000668
	(0.00370)	(0.00361)	(0.00111)	(0.00106)
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Pre-policy mean outcome	0.395	0.381	0.099	0.088
Observations	33,434,377	33,434,377	33,434,377	33,434,377

Notes: The sample is restricted to the jurisdictions that report each month of the year. The dependent variable is the number of crimes per 100,000 people as reported in each column. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F6: Effects of opioid reformulation on temperature and crimes. Alternative fixed effects.

	Daily crimes per 100,000 people								
	Violent crimes	Assault	Rape	Homicides	IPV	Monetary crimes	Robbery	Fraud	Gambling
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature × Opioid exposure	0.0218***	0.0215***	0.00026	0.00007	0.00438***	0.0267***	0.00099	-0.00106	0.0000455
	(0.0032)	(0.0031)	(0.00027)	(0.00007)	(0.00099)	(0.0042)	(0.00068)	(0.00098)	(0.0000597)
Temperature × Opioid exposure × Post-2010	-0.0205***	-0.0202***	-0.00024	-0.00007	-0.00405***	-0.0247***	-0.00096	0.00110	-0.0000502
	(0.0030)	(0.0029)	(0.00028)	(0.00007)	(0.00095)	(0.0041)	(0.00066)	(0.00098)	(0.0000600)
Observations	37,799,936	37,799,936	37,799,936	37,799,936	37,799,936	37,799,936	37,799,936	37,799,936	37,799,936
Pre-policy outcome mean	0.304	0.294	0.0096	0.0009	0.077	0.787	0.030	0.068	0.0003
Jurisdiction-Day-of-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of crimes per 100,000 people. *Post-2010* is a dummy variable equal to 1 for the post-reformulation period, starting from 2010. *Opioid exposure* is the county-level pre-2010 exposure to opioids. Standard errors are clustered at the county level. All regressions are weighted using jurisdiction population weights. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F7: Effects of substance abuse regulation policies on temperature-assault involving substances

	Assaults per 100,000 people				
	Any substance	Alcohol	Heroin	Cocaine	Marijuana
	(1)	(2)	(3)	(4)	(5)
Panel A: SAT facilities					
Temperature × SAT	-0.0001***	-0.0001***	0.0000001	-0.0000002	-0.000002*
	(0.00002)	(0.00002)	(0.0000002)	(0.0000004)	(0.000001)
Mean Outcome	0.0694	0.0652	0.00002	0.0001	0.0007
Observations	26,879,916	26,879,916	25,367,771	25,367,771	25,367,771
Panel B: Opioid reformulation					
Temperature × Opioid exposure	0.0056***	0.0055***	0.00000140	-0.00000903	0.00005870
	(0.0008)	(0.0008)	(0.00000668)	(0.00002840)	(0.00004160)
Temperature × Opioid exposure × Post-2010	-0.0057***	-0.0056***	-0.00000169	0.00000957	-0.00005820
	(0.0008)	(0.0008)	(0.00000669)	(0.00002840)	(0.00004160)
Pre-policy mean outcome	0.0369	0.0342	0.00001	0.0001	0.0004
Observations	38,033,629	38,033,629	35,768,587	35,768,587	35,768,587

Notes: Table reports on our baseline specifications, respectively Equation (1) and Equation (2) in Panel A and B on the number of assaults involving substances in a jurisdiction per 100,000 people. Panel A controls for jurisdiction-month-year, day-of-week, day-of-week, week-of-year fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-month-year, day-of-week, day-of-year, week-of-year fixed effects and state- and year-specific temperature and precipitation effects. All regressions are weighted using jurisdiction population weights. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F8: Effects of substance abuse regulation policies on temperature-intimate partner violence involving substances

	Intimate partner violence cases per 100,000 people				
	Any substance	Alcohol	Heroin	Cocaine	Marijuana
	(1)	(2)	(3)	(4)	(5)
Panel A: SAT facilities					
Temperature × SAT	-0.00005***	-0.00005***	-0.0000001	-0.0000001	0.0000003
	(0.00001)	(0.00001)	(0.00000008)	(0.0000002)	(0.0000005)
Mean Outcome	0.0285	0.0271	0.00000	0.00003	0.0002
Observations	26,879,916	26,879,916	25,367,771	25,367,771	25,367,771
Panel B: Opioid reformulation					
Temperature × Opioid exposure	0.0020***	0.0021***	-0.000000917	-0.00000281	0.00000078
	(0.0004)	(0.0004)	(0.00000191)	(0.0000113)	(0.0000273)
Temperature × Opioid exposure × Post-2010	-0.0021***	-0.0021***	0.000000577	0.00000302	-0.000000212
	(0.0004)	(0.0004)	(0.00000193)	(0.0000114)	(0.0000274)
Pre-policy mean outcome	0.0142	0.0133	0.00001	0.00001	0.0001
Observations	38,033,629	38,033,629	35,768,587	35,768,587	35,768,587

Notes: Table reports estimates of our baseline specifications, respectively Equation (1) and Equation (2) in Panel A and B on the number of intimate partner violence cases involving substances in a jurisdiction per 100,000 people. Panel A controls for jurisdiction-month-year, day-of-week, day-of-week, week-of-year fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-month-year, day-of-week, day-of-year, week-of-year fixed effects and state- and year-specific temperature and precipitation effects. All regressions are weighted using jurisdiction population weights. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F9: Effects of opioid reformulation on temperature and other crimes by State Medical Marijuana Law

	Medical Marijuana Law			
	Rape		Homicide	
	Without	With	Without	With
	(1)	(2)	(3)	(4)
Temperature × Opioid exposure	0.000790***	-0.000177	0.000180**	-0.000109
	(0.000306)	(0.000609)	(0.0000755)	(0.000141)
Temperature × Opioid exposure × Post-2010	-0.000795***	0.000172	-0.000180**	0.0000960
	(0.000307)	(0.000614)	(0.0000757)	(0.000141)
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Observations	26,394,328	7,144,196	26,394,328	7,144,196
Pre-policy mean outcome	0.006	0.133	0.001	0.013

Notes: Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F10: Effects of opioid reformulation on temperature-crimes by time of the day

	Time of the day			
	Morning	Afternoon	Evening	Night
	(1)	(2)	(3)	(4)
Panel A: Violent Crimes				
Temperature × Opioid exposure	0.00333***	0.00671***	0.0163***	0.00847***
	(0.000832)	(0.00100)	(0.00192)	(0.00113)
Temperature × Opioid exposure × Post-2010	-0.00336***	-0.00677***	-0.0164***	-0.00855***
	(0.000832)	(0.000994)	(0.00191)	(0.00112)
Pre-policy mean outcome	0.048	0.089	0.106	0.063
Panel B: Assaults				
Temperature × Opioid exposure	0.00327***	0.00666***	0.0162***	0.00806***
	(0.000809)	(0.00101)	(0.00188)	(0.00109)
Temperature × Opioid exposure × Post-2010	-0.00329***	-0.00672***	-0.0163***	-0.00813***
	(0.000809)	(0.000999)	(0.00187)	(0.00108)
Pre-policy mean outcome	0.046	0.087	0.103	0.060
Panel C: Intimate Partner Violence				
Temperature × Opioid exposure	0.000549**	0.00114***	0.00327***	0.00231***
	(0.000248)	(0.000380)	(0.000519)	(0.000425)
Temperature × Opioid exposure × Post-2010	-0.000550**	-0.00115***	-0.00331***	-0.00233***
	(0.000248)	(0.000379)	(0.000517)	(0.000423)
Pre-policy mean outcome	0.012	0.018	0.028	0.018
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Observations	38,786,501	38,786,501	38,786,501	38,786,501

Notes: Table reports the coefficients on the interaction between temperature and opioid exposure and temperature, opioid exposure, and a dummy variable that takes value equal to one after 2010 estimating Equation (2). The outcome variable is the number of violent crimes (in Panel A), of assaults (Panel B), and of intimate partner violence on females (Panel C) in a jurisdiction per 100,000 people, based on the time of the day during which they occurred. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table F11: Effects of opioid reformulation on temperature-crimes by day of the week

	Day of the week					
	Violent Crime		Assaults		Intimate Partner Violence	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × Opioid exposure	0.0312***	0.0443***	0.0305***	0.0435***	0.00604***	0.0121***
	(0.00417)	(0.00525)	(0.00409)	(0.00510)	(0.00118)	(0.00182)
Temperature × Opioid exposure × Post-2010	-0.0317***	-0.0450***	-0.0310***	-0.0442***	-0.00613***	-0.0122***
	(0.00411)	(0.00518)	(0.00403)	(0.00504)	(0.00116)	(0.00180)
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓
Observations	27,160,381	10,873,248	27,160,381	10,873,248	27,160,381	10,873,248
Pre-policy mean outcome	0.292	0.336	0.282	0.325	0.070	0.095

Notes: Columns 1-3-5 report estimates on crimes occurred during weekdays (Monday through Friday), columns 2-4-6 report estimates on crimes occurred during weekends (Saturday and Sunday). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

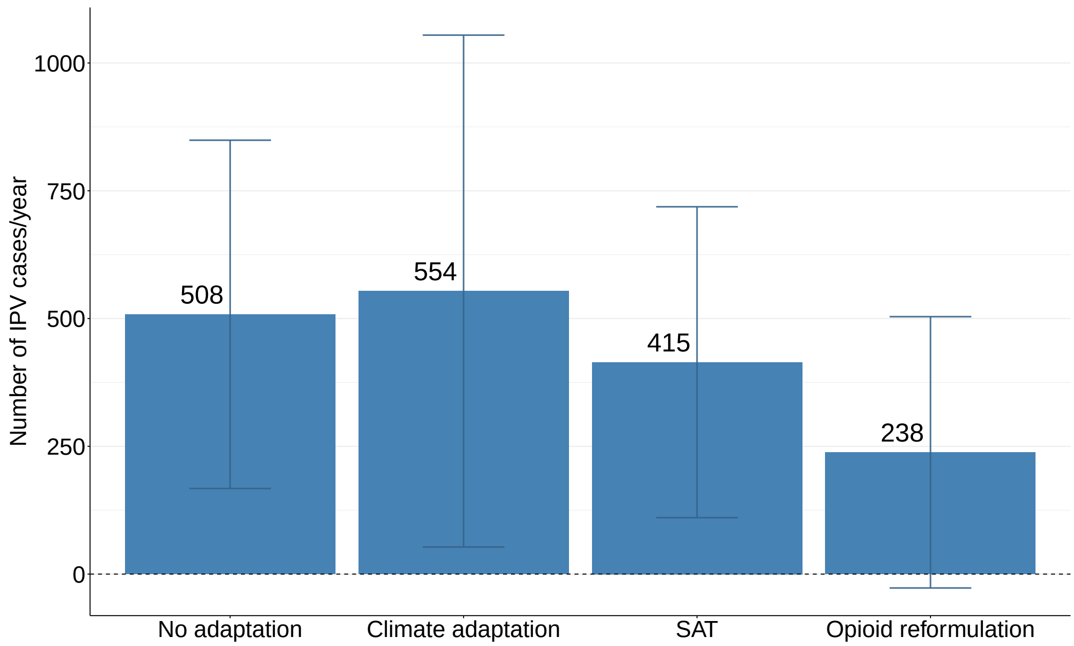
Table F12: Effects of opioid reformulation on temperature-crimes by crime characteristics

	Characteristics of crime					
	No Firearm	Firearm	Outside	Home	Outdoor	Indoor
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Violent Crimes						
Temperature × Opioid exposure	0.0261***	0.0011***	0.0129***	0.0171***	0.0033***	0.0200***
	(0.0031)	(0.0004)	(0.0018)	(0.0024)	(0.0005)	(0.0029)
Temperature × Opioid exposure × Post-2010	-0.0265***	-0.0011***	-0.0132***	-0.0174***	-0.0034***	-0.0203***
	(0.0031)	(0.0004)	(0.0018)	(0.0024)	(0.0005)	(0.0028)
Pre-policy mean outcome	0.2330	0.0105	0.0979	0.1881	0.0160	0.2339
Panel B: Assaults						
Temperature × Opioid exposure	0.0255***	0.0010**	0.0128***	0.0166***	0.0032***	0.0196***
	(0.0030)	(0.0004)	(0.0018)	(0.0023)	(0.0005)	(0.0028)
Temperature × Opioid exposure × Post-2010	-0.0259***	-0.0010***	-0.0131***	-0.0169***	-0.0033***	-0.0199***
	(0.0030)	(0.0004)	(0.0018)	(0.0023)	(0.0005)	(0.0027)
Pre-policy mean outcome	0.2232	0.0098	0.0957	0.1807	0.0154	0.2255
Panel C: Intimate Partner Violence						
Temperature × Opioid exposure	0.0061***	0.0001	0.0012***	0.0054***	0.0002	0.0056***
	(0.0010)	(0.0000864)	(0.0003)	(0.0009)	(0.0001)	(0.0010)
Temperature × Opioid exposure × Post-2010	-0.0062***	-0.0001	-0.0012***	-0.0054***	-0.0002	-0.0057***
	(0.0010)	(0.0000864)	(0.0003)	(0.0009)	(0.0001)	(0.0010)
Pre-policy mean outcome	0.0648	0.0011	0.0120	0.0628	0.0026	0.0669
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Year FE	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓
Observations	38,033,629	38,033,629	38,033,629	38,033,629	38,033,629	38,033,629

Notes: The dependent variable is the number of crimes per 100,000 people by characteristics. Temperature is the average daily temperature measured in degrees Celsius (°C). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

G Back-to-the-envelope estimates: additional results

Figure G1: Annual cases of Intimate Partner Violence from a 1°C increase in temperature



Notes: The figure reports estimated annual cases of intimate partner violence induced by a 1°C increase in temperature. Although outcome and climate data are available until 2023, estimates are based on the 2006-2017 sample, when information on substance abuse treatment (SAT) facility availability is observed and prior to the opioid reformulation we lack measures of prescription opioid exposure. Restricting the sample to this period ensures comparability across the four specifications. The "No adaptation" bar reflects the estimated direct effect of temperature on IPV. The "Climate adaptation" bar allows the temperature-IPV relationship to vary by terciles of long-run average temperature. The "SAT" bar incorporates both the direct temperature effect and its interaction with SAT expansion (Equation (1)). The "Opioid reformulation" bar is based on estimates from Equation (2). Error bars denote 95% confidence intervals.