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

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Abstract

Higher temperatures can physiologically exacerbate the effects of substance abuse, increasing risks of impaired cognitive functions and violent behavior. Using administrative crime data and daily temperatures across U.S. counties between 1991 and 2023, we show that two public policies regulating substance abuse substantially moderate the impact of temperature on violent crimes that involve social interactions. We monetize the ancillary policy benefits for the case of intimate partner violence, the most widespread crime in the U.S., and show that regulations targeting substance abuse can be a cost-effective tool for climate adaptation.

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

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1 Introduction

Higher temperatures pose growing challenges for public health, safety, and economic wellbeing. A central task for policymakers is to design adaptation policies that mitigate these damages efficiently. In a theoretically justified welfare-maximizing framework, adaptation policies are evaluated through standard cost-benefit analysis and should include both direct and ancillary effects (Carleton et al., 2024). Within this framework, two broad classes of adaptation policies emerge: policies explicitly designed to reduce climate damages (e.g., cooling centers, seawalls), and policies not designed for adaptation but that nevertheless can generate ancillary adaptation benefits (e.g., public health facilities, social safety nets).

A large body of evidence shows that higher temperatures increase aggression and violent behavior (e.g., Anderson, 1987, 2001; Kenrick and MacFarlane, 1986; Ranson, 2014). Among policies not explicitly designed for adaptation, interventions that curb substance abuse may play an important adaptive role. Alcohol, opioids, and other illicit substances can impair cognitive and emotional functions, and higher temperatures can both increase their use (Cohen and Gonzalez, 2024), and amplify their effects through psychological and physiological channels (Chang et al., 2023; Hensel et al., 2021; Jhang et al., 2025; Parks et al., 2023), leading to an increase in aggressiveness and violent behavior (Luca et al., 2015). As a result, policies targeting substance abuse may generate ancillary adaptation benefits by moderating temperature-induced violent behavior.

In this paper, we ask 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 address this question by studying two major public policies in the U.S. that address abuse of substances, including alcohol and opioids. We explore the effect of these policies, respectively by exploiting variation in the opening of new substance abuse treatment facilities across counties between 1998 and 2016, and by leveraging a nation-wide policy intervention in 2010 that reformulated the main legal opioid, OxyContin, to address the overprescription of opioids and mitigate their addictive risks. We combine the variation induced by the policy environment with daily short-term temperature fluctuations to estimate the moderating impact of the policies on the temperature-crime relationship.

Our analysis starts by presenting four empirical facts that inform our empirical approach. Using administrative data from the FBI's National Incident-Based Reporting System from 1991 to 2023, we document that temperature is positively associated with higher crime rates: 1°C increase in daily average temperature is associated with 0.0047 additional crimes per 100,000 people (about 0.7% relative to the sample mean). The effect is more pronounced for violent crimes—including intimate partner violence—rather than monetary crimes (1% vs 0.5%, respectively), and weak and imprecise for crimes where interactions between victims and offenders are limited or absent (e.g., fraud). Second, we provide evidence that higher temperatures increase substance abuse. On the one hand, using survey data we show that higher temperatures are positively associated with alcohol consumption and heavy drinking. We also show that this effect is more pronounced in more opioid exposed counties, in line with previous evidence on the complementarity of the two substances ("polysubstance use") (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 test whether higher temperatures can also physiologically accentuate the effect of substances by leading to more violent behavior. We show that higher temperature are associated with more violent crimes with offenders under substances, especially alcohol, cocaine, marijuana and stimulants. Finally, we show that the temperature–violent crime gradient is systematically steeper in counties with higher baseline substance exposure. These patterns indicate that substance use is a major channel in the temperature-crime relationship.

Our main empirical approach allow us to identify the moderating effects of substance abuse regulations under the assumption that the temperature-crime relationship would have remained the same absent the policy changes. In our most restrictive specification, we allow for the effect of temperature and precipitation to vary across time and location, so as to account for annual changes and location-specific differences in the direct effects of temperature and precipitation. We find that a 1°C increase is associated with 0.0004 fewer violent crimes per 100,000 people after the opening of an additional SAT per 100,000 people, corresponding to about 25% of the direct effect of temperature. Similarly, a 1°C increase is associated with 0.0127 fewer cases per 100,000 people after the opioid reformulation, offsetting the pre-policy additional temperature-driven violent crimes occurring in opioid exposed counties. The event-study analysis documents that the attenuating role of the policy persists over ten years. Taken together, the evidence indicates that policies aimed at reducing substance abuse generate sizable ancillary adaptation benefits by dampening the behavioral response to climatic stress.

We also explore several mechanisms through which these policies may have mitigated the temperature–violent crime gradient. First, we find that both policies reduce substance-involved violent crime on hot days. For SAT facility expansion, the mitigating effect applies to alcohol- and marijuana-related offenses. By contrast, the mitigating effect of the OxyContin reformulation is concentrated in alcohol-related violent crime. This pattern suggests that the reformulation reduced co-use of alcohol among opioid users during hot days, consistent with complementarities in substance abuse.

Second, we show that the effectiveness of substance-abuse policies depends on the scope for substitution across drugs. For SAT expansion, which targets multiple substances simultaneously, we find no evidence of substitution toward specific drugs. In contrast, the mitigating effect of the OxyContin reformulation is muted in settings with 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. These findings align with evidence that marijuana can serve as a substitute for opioids (Evans et al., 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 is consistent with individuals living in warmer climates having greater physiological tolerance to higher temperatures, therefore potentially mitigating the compounding effect of temperature and substance abuse on violent behavior.

Fourth, we show that the moderating effect of both policies is not driven by changes in the timing of criminal activity: the reduction appears across all hours of the day. Finally, the effect is substantially larger on weekends than weekdays, consistent with prior work documenting that both substance consumption and temperature-related violent crime peak when individuals can adjust their schedule more easily (Cohen and Dechezleprêtre, 2022; Kuntsche and Labhart, 2012; Yan and Kuo, 2019).

We conclude by quantifying the ancillary benefits of these policies. Focusing on intimate partner violence—one of the most prevalent and socially costly violent crimes—we estimate the willingness to pay for the OxyContin reformulation to avoid temperature-induced intimate partner violence. We find that the reformulation generated approximately \$35.3 billion (2023 USD) in aggregate social benefits for a 1°C increase in average daily temperature. These ancillary adaptation benefits are not reflected in standard evaluations of either substance-abuse or climate policies, underscoring the importance of accounting for cross-policy spillovers when assessing the social value of interventions.

Our findings contribute to a well established literature that examines the effect of temperature on violent behavior, one of the main channels of the socio-economic impact 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; Heilmann et al., 2021; Mukherjee and Sanders, 2021; Ranson, 2014). We contribute to this strand of the literature by documenting a strong positive linear relationship between daily temperature and violent crime in the United States over more than thirty years. The effect is robust for crimes involving close social interaction, including intimate partner violence, a relationship that has never been documented before in the U.S. We also show that the higher temperatures increase violent crimes involving substance use (e.g., alcohol, drugs), and differentially more in areas more exposed to the opioid epidemic, highlighting substance abuse as a central channel linking heat and violent behavior.

Our paper also contributes to the literature evaluating public policies that do not target adaptation but have consequences on mitigating climate impacts on socio-economic outcomes (Carleton et al., 2024). The vast majority of prior work exploits changes in budget constraints through cash transfers programs or income shocks to study how these interventions mitigate the impact of temperatures on education and labor market outcomes (Adhvaryu et al., 2024; Garg et al., 2020), 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., 2020). 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, 2023). We provide first evidence of successful examples of adaptation in the context of crime and violence. Prior reviews suggest limited evidence of ex ante adaptation on crime, violence, conflicts, and suicide (Burke et al., 2015; Carleton and Hsiang, 2016; Carleton et al., 2024). By isolating one of the exact mechanisms of the temperature-crime relationship, substance abuse, we quantify and monetize the ancillary benefits of substance abuse regulation policies as a mediator to the temperature-crime relationship.

Finally, our paper contributes to the literature evaluating policies that regulate substance use. 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 contribute by showing that SAT facilities also moderate the behavioral response to heat, generating previously undocumented adaptation co-benefits and thus increasing the cost-effectiveness of this intervention. We also contribute to the growing literature on the U.S. opioid epidemic (Arteaga and Barone, 2022; Dave et al., 2025; Evans et al., 2019). Recent studies document that supply-side interventions, such as the reformulation of OxyContin or must-access prescription drug monitoring programs, had unintended consequences, including increases in child maltreatment and foster care entry (Evans et al., 2022; Gihleb et al., 2022), as well as broader political effects (Arteaga and Barone, 2025). In contrast, we show that the OxyContin reformulation also generated a sizable positive adaptation spillover by attenuating the temperature–violent crime gradient. Thus, 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

We describe the data we use 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 at the county-day level 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 at the individual-, county-, and state-level to explore mechanisms and channels of the relationship between temperatures, substance abuse, and crime.

2.1 Crime data

We use data from the FBI's National Incident-Based Reporting System (NIBRS) for the period 1991-2023. 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.

Leveraging the reported offenses within each incident, we build offense-specific daily counts.[1] Broadly, we group offenses into two main categories: violent and monetary

[1] 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 offenses per incident. Accordingly, we treat each incident as one crime when constructing overall crime counts. However, when building offense-

crimes. The former include assault, rape, and homicide; the latter include 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.[2]

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.

NIBRS further indicates whether the offender was under the influence of substances at the time of the crime. This information is directly available for alcohol and any unspecified drugs. We refine our categorization of drug-related crimes by using detailed information on the type of drugs seized from the offender, including heroin, cocaine, marijuana, stimulants, hallucinogens (e.g., in a "heroin-involved" crime, the offender was reported under the influence of drugs and heroin was seized during the incident).[3]

The number of agencies reporting data is increasing over time, ranging 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 at the year level, and we provide robustness analyses exploiting within-year variation to test for consistency of our estimates.

A common problem in the use of administrative data is that they may misrepresent criminal incidence if, for example, police effectiveness or police ability to gather evidence were also a function of weather. In this case, temperatures could have an influence on crime data collection. Another potential concern would arise if people alter their reporting

specific measures, we count each reported offense separately. For example, if an incident involves assault and vandalism, it is recorded as one total crime and as one offense in each respective category.

[2]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.

[3]We cannot rule out over-reporting or under-reporting of specific drugs, especially in cases of polysubstance use.

behavior as a function of temperatures. In these cases, sample selection could be confounding the relationship between crime rate and temperatures. While we cannot directly rule out these mechanisms in our setting, prior work has documented that they play a marginal role in the temperature-crime relationship (e.g., Cohen and Gonzalez, 2024; Heilmann et al., 2021). In our setting, we show that altering our fixed effects both spatially and temporally—and thus capturing different potential unobserved changes in evidence gathering, police effectiveness, and reporting—does not alter our baseline findings.

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 ($\approx$ 11km). We combine weather data with 30 arc-seconds ($\approx$ 1km) population density information (Seirup and Yetman, 2006) to compute the county-level population-weighted average daily temperature and total precipitation.

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. The CBP reports the number of SAT establishments in each county, but only for counties with at least one active facility.[4] For the main analysis, we restrict the

[4]Beginning in 2017, the CBP reports only counties with three or more SAT facilities, which is why our

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 two alternative treatment definitions: (i) an indicator for whether a SAT facility opened in the county in the previous year, and (ii) an indicator for the first SAT facility opening in the county. Figure A2 reports the total number of SAT establishments over time, steadily increasing over time. Figure A3 then reports their distribution across the country, weighted by population. Between 1998 and 2016, U.S. counties, on average, report 6.14 SAT establishments 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 Oycontin reformulation

Our second policy of interest concerns the exogenous reduction in access to prescription opioids following the reformulation of OxyContin in 2010. Opioid prescriptions in the U.S. increased sharply from 76 million in 1991 to over 250 million in 2010 (Volkow et al., 2014). OxyContin, introduced by Purdue Pharma in 1992, was a key driver of this expansion. The drug contained oxycodone—a narcotic analgesic originally prescribed for moderate to severe chronic pain—but also carried a high risk of addiction and misuse. To address growing concerns about substance abuse, Purdue Pharma developed an abuse-deterrent formulation designed to make the pills harder to crush or dissolve and take via non-oral routes. The U.S. Food and Drug Administration approved this new version in April 2010, and distribution began in August 2010, when the original formulation was discontinued without 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 this nationwide reformulation of OxyContin in 2010—an unanticipated,

analysis ends in 2016.

unilateral decision by Purdue Pharma—as an exogenous policy shock to opioid access.

To measure pre-reformulation exposure to prescription opioids, we use the population-weighted average number of Schedule II opioid prescriptions per capita during 2006-2009, obtained from the Centers for Disease Control and Prevention. The CDC data represent an 85% sample of retail pharmacy providers but exclude hospitals. 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 maps the spatial distribution of population-weighted average number of opioid prescriptions per capita in the pre-reformulation period. The mean opioid prescription rate was 0.85 per capita, and about 30% of counties had more than one prescription per resident.

As an alternative source, we 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. From ARCOS, we compute the average number of Schedule II opioid pills distributed and the number of shipments per capita over 2006-2009. We use these alternative measures to assess the robustness of our findings to alternative measures of opioid exposure.

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.[5] The survey includes information on whether respondents consumed alcohol in

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

the past months, and, if so, 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. We use state-level information on the timing of medical marijuana legalization from the National Conference of State Legislatures to evaluate whether the availability of marijuana as a therapeutic substitute moderates the effects of substance abuse policies on the temperature-crime relationship.

Socio-demographic characteristics. Finally, we complement our main data set with a rich set of county-level socio-demographic covariates. We obtain the share of the population living in rural areas from the 2010 Census Bureau. We also use median household income from the Economic Research Service at the U.S. Department of Agriculture and county labor force statistics from the Bureau of Labor Statistics.

3 Motivating facts: Temperatures, crimes, and substance abuse

Temperature increases can affect violent behavior through multiple channels. The most direct mechanism operates through physiological and psychological effects on impulse controls and aggression (Anderson, 1987, 2001; Kenrick and MacFarlane, 1986). Higher temperatures can deteriorate mental health, increase anxiety, despair and isolation (Mullins and White, 2019), and in turn raise the propensity to use substances such as alcohol and opioids (Gros et al., 2013; Martins et al., 2012), and induce aggression and violent behavior (Dave et al., 2025; Deiana and Giua, 2021; Luca et al., 2015).

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). Second, conditional on consumption, higher temperatures may amplify the physiological consequences of substances through blood vessel dilatation and blood pressure increase, thereby increasing violent behavior (Herrnstein and Wilson, 1985; Miczek et al., 2004; Sim, 2023). Both mechanisms would imply that policies that regulate substance abuse could attenuate the sensitivity of 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).

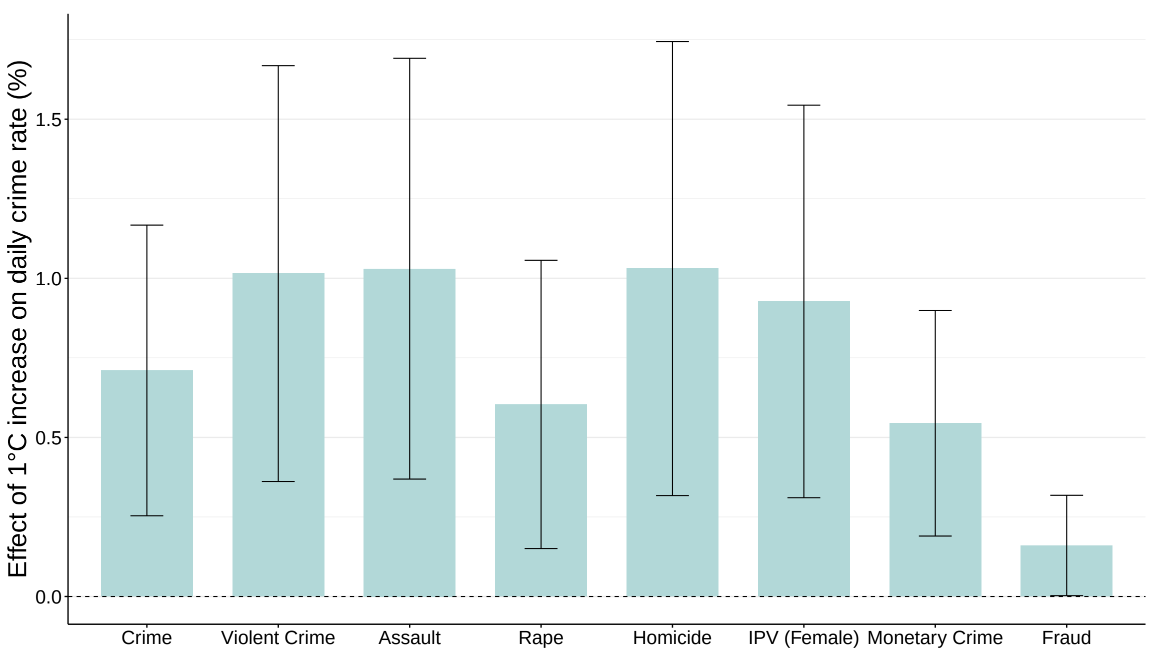
Temperatures increase crime. We begin by documenting the well-established relationship between temperature and crime in our data. Using data over more than thirty years across U.S. jurisdictions, we estimate the relationship between daily temperatures and different categories of crime. We exploit jurisdiction-day-month variation, while accounting for day-of-week and month-of-year fixed effects (see Appendix B for additional details).[6]

Figure 1 displays the estimated coefficients (normalized by the weighted sample average). 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 only 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 (0.02% at the mean).

[6] In Appendix B, we assess alternative functional forms for temperature and precipitation and find no evidence against linearity, consistent with prior studies on temperature and crime (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.

Altogether, these results are consistent with prior evidence from Mexico and the United States (Cohen and Gonzalez, 2024; Colmer and Doleac, 2023; Heilmann et al., 2021; Ranson, 2014), which attributes the temperature-crime relationship primarily to interpersonal and affective channels rather than economic motives. 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 United States through 1991 and 2023



Notes: The figure plots the coefficients of temperature on crime rates per 100,000, across different categories of crimes. The coefficients (in teal) are normalized by the weighted sample mean. The regressions control for daily total precipitation, and jurisdiction-day-month, month-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 B1 reports the unweighted coefficients.

Temperatures increase substance abuse. We next provide two pieces of evidence consistent with one physiological mechanisms linking temperatures to violent behavior: increase substance use. 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—defined as at least 28 (56) drinks in the previous month for women (men)—by 0.04-0.06 percentage points, corresponding to a 0.58-0.77% increase relative to the mean (Table 1, columns 1-3).

Since alcohol consumption is strongly associated with prescription opioid misuse and overdose (Esser et al., 2019, 2021), we examine whether the temperature–alcohol relationship varies by local opioid exposure. We find 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 in less exposed counties is smaller and not statistically significant. 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 intensity substance-related harms for alcohol and opioid consumption. These results support the hypothesis that temperature affects violent crime partly by increasing substance use and its phys-

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

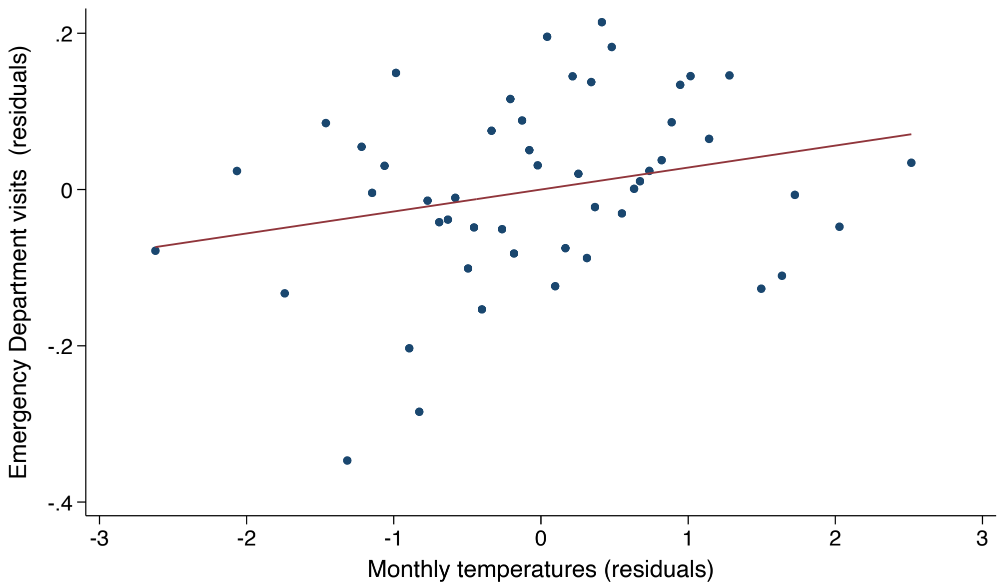
	Heavy Drinking (0/1)			
	(1)	(2)	(3)	(4)
30-day Temperature	0.000468***	0.000569***	0.000425**	0.000336
	(0.000)	(0.000)	(0.000)	(0.000)
30-day Temperature × High opioid exposure				0.000325**
				(0.000)
30-day Precipitation	0.00263	0.0131	0.0143*	-0.0178
	(0.006)	(0.008)	(0.008)	(0.0110)
Period	1991-2012	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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

iological consequences, mechanisms that substance abuse regulations could potentially mitigate.

Temperatures increase substance-involved crime. Building on the 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 the rate of

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



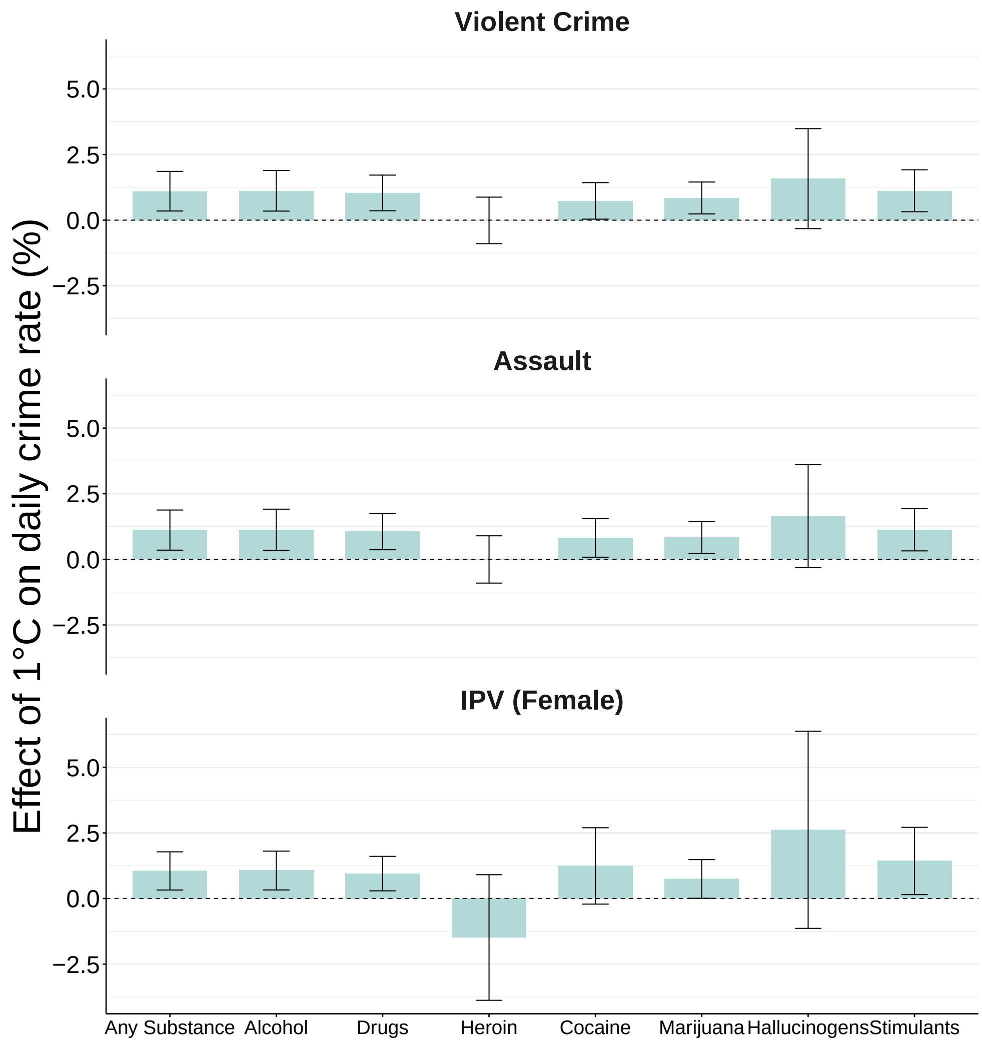
Notes: Figure shows binned scatterplots with 50 bins and a linear regression (coefficient = 0.0281, standard error = 0.0138) on the underlying data on the correlation net of state-month, state-year, month-year fixed effects between residualized monthly rate of emergency department visits for nonfatal 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).

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 offenses involving cocaine, marijuana, and stimulants, and imprecisely estimated for hallucinogens, whereas those for heroin-related offenses are small and not significant across crime categories.

Substances amplify the effect of temperatures on crimes. Finally, we combine evidence on substance use, temperatures, and violent behavior to test whether the temperature-

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

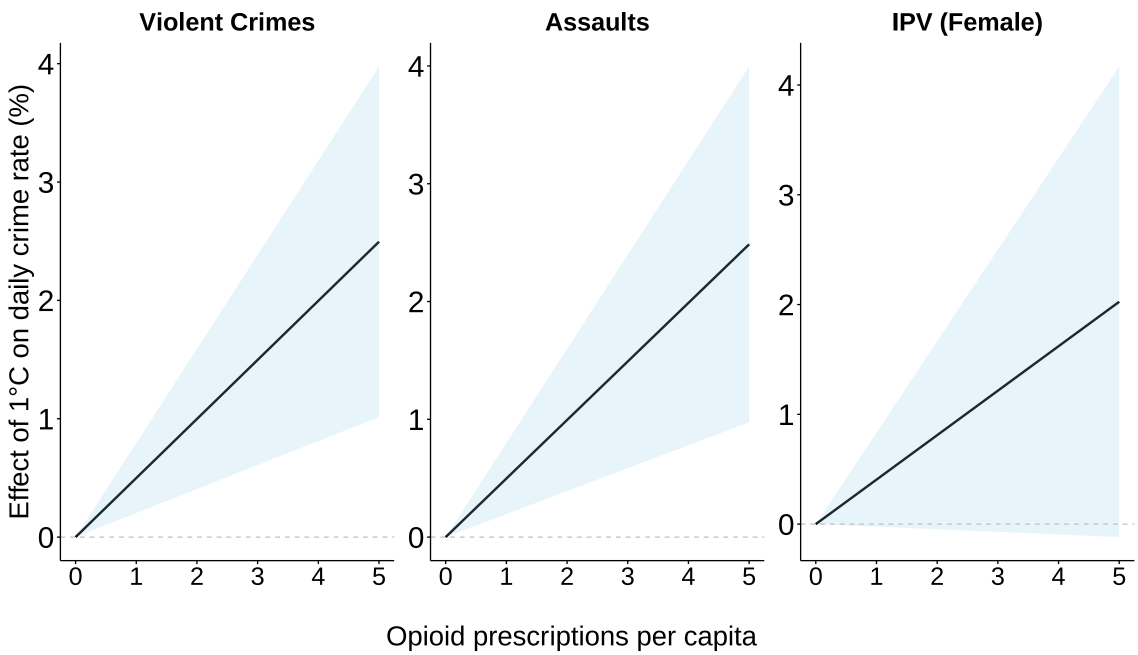


Notes: The figure plots the coefficients of temperature on crime rates per 100,000 people for different categories of crimes. The coefficients (in teal) are normalized by the weighted sample mean. The regressions control for daily total precipitation, and jurisdiction-day-month, month-year, and day-of-week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

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 amplifies the behavioral and psychological effects of higher temperatures on aggressions.

Collectively, these four empirical patterns point to substance use as a key mechanism linking heat to crime, motivating our analysis of how regulatory interventions can attenuate this relationship.

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



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

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

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

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. $SAT_{c(i)t-1}$ captures the number of SAT facilities per 100,000 people in county c, lagged one year to ensure that openings precede observed crime outcomes. In alternative specifications, we use alternative measures for substance abuse treatment such as the first-ever opening of a treatment facility in the county, thereby capturing the extensive margin of treatment access rather than its changes in the intensive margin.

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 $\times$ day-month fixed effects, μ_{idm}, that absorb differences in crime seasonality within each jurisdiction for a given day-month (e.g., Chicago Police Department on September 1 across years); month $\times$ year fixed effects, λ_{mt}, that capture nationwide shocks common to all jurisdictions in a given month; day-of-week fixed effects, κ_{dw}, that account for systematic intra-week variation in criminal activity and reporting practices; and jurisdiction-year fixed effects, ϕ_{it}, that absorb any time-varying local determinant of crime potentially correlated with temperature trends (e.g., policing intensity, demographic shifts, or reporting practices).[7]

A remaining concern is that there are remaining unobserved differences in how temperature affects crime across years or regions that are correlated with the opening of new SAT facilities. To address this concern, we flexibly allow the marginal effects of temperature and precipitation to vary by county (e.g., temperatures in 2002 and 2012 have different effects regardless of policy changes), and by year (e.g., temperatures in Boston and Chicago have different effects). Altogether, identification of β comes solely from within-jurisdiction-day variation in weather over time, effectively comparing, for instance, how violent crimes in Chicago respond to temperature fluctuations in years with different numbers of SAT, holding constant all unobserved jurisdiction- or year-specific factors that might affect both SAT openings and the temperature–crime relationship.

All regressions are weighted by population in the jurisdiction, and we cluster standard errors at the county-level.

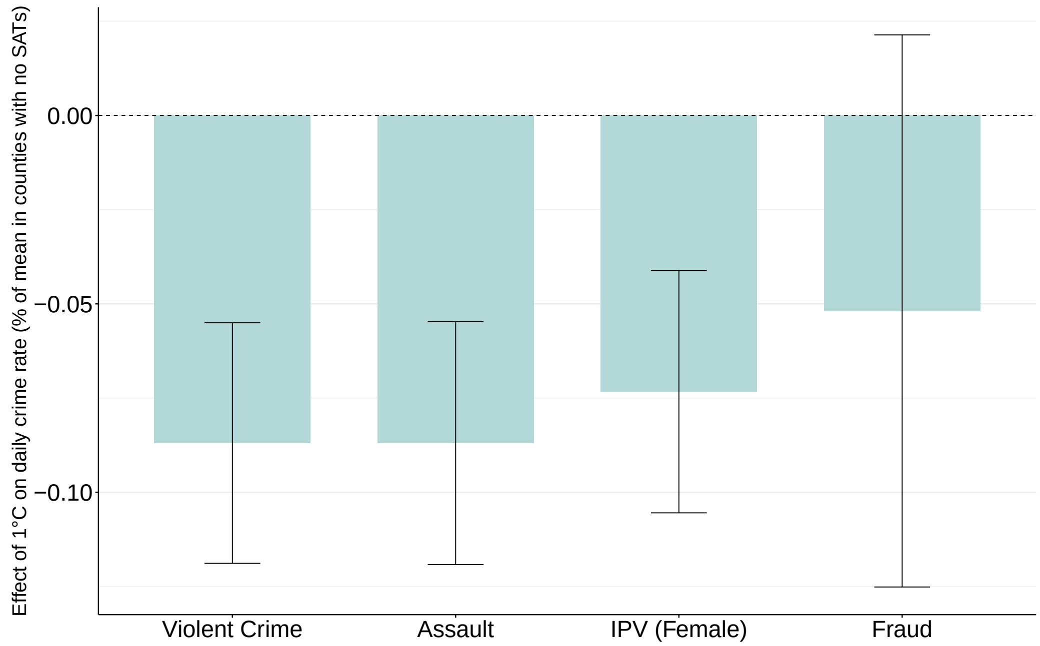
4.2 Results

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 E1). We find that opening one additional SAT facility per 100,000 residents reduces the effect of a 1°C increase in temperature on total violent crime by 0.0004 incidents per 100,000 people—equivalent to about 0.09% of the daily average number of violent crimes in counties without any facility. Compared with our baseline estimates (Table B1), this implies that approximately 25% of the temperature effect is offset. The mitigating effect is similar in magnitude for assaults and intimate partner violence, but it is not statistically different from zero for fraud, consistent with the hypothesis that SAT facil-

[7] Because the number of SAT facilities varies at the county–year level, the uninteracted coefficient is absorbed by these fixed effects. In Appendix E, we present results from a less conservative specification that does not include county-year fixed effects, identifies the direct effect of SAT facilities on crime.

ities primarily reduce temperature-induced crimes involving physical interaction between victims and offenders.

Figure 5: The mitigating effect of substance-abuse treatment facilities on the temperature-crime relationship



Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature and number of substance abuse treatment (SAT) facilities per 100,000 people in a regression where the outcome variable is the number of crime 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-day-month, jurisdiction-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.

Robustness. We perform several robustness checks that we report in Appendix E. First, we expand the sample to include counties—and therefore agencies—not reported as hosting any SAT facility between 1998 and 2016 in the CBP data (Table E2). Results remain consistent, if anything slightly larger in magnitude and more precisely estimated. Second, we find similar estimates when we restrict the sample to agencies that report crimes in every month of the year (Table E3). Third, we redefine the treatment to capture the first-ever opening of a SAT facility in a county (Table E4). In this specification, the interaction effect is statistically insignificant across crime categories, suggesting that the mitigating effect primarily operates along the intensive rather than the extensive margin.

Finally, we test the sensitivity of our findings to alternative fixed effects (Table E5). In Panel A, we relax our baseline identification assumption, allowing for the estimation of the direct effect of SAT facilities on crime. An additional SAT facility per 100,000 residents reduces daily violent crimes by 0.029 incidents per 100,000 people.[8] We also find that a 1°C increase in daily average temperature amplifies the direct effect of an additional SAT facility by about 3%. The magnitude of the estimated coefficients remains similar across subcategories of violent crimes—assault and intimate partner violence. Fraud exhibits a significant positive coefficient for the direct effect of SAT facilities. 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 for fraud is also statistically significant, its magnitude is small. In Panel B, we replace month–year and day-of-week fixed effects with date fixed effects. In Panel C, we exploit within-jurisdiction, within-month-year variation by including jurisdiction–month–year fixed effects and controlling for day-of-week and week-of-year fixed effects, while holding the rest of the specification as in the baseline. Results remain consistent for violent crime, assault, and intimate partner violence, and the interaction coefficient for fraud becomes statistically insignificant once we introduce interactions of temperature and precipitation with county and year dummies.

Taken together, these results highlight the mitigating role of new substance abuse treatment facilities in moderating the relationship between temperature and violent crime, underscoring the importance of interventions that regulate and reduce substance abuse.

[8] This result is very similar to Bondurant et al. (2018), who document a 0.12–0.34% reduction in monthly violent crimes for an additional SAT

Heterogeneity. Given the specific channel explored—substance abuse—the mitigating effects of treatment facilities may differ systematically with local socioeconomic conditions. We examine this heterogeneity along several dimensions, including urbanization, education, income, and labor force participation (Table E6).

The mitigating effects of SAT facilities on temperature-related crimes are concentrated in urban areas (columns 1-2, Panel A). This pattern likely reflects a combination of higher baseline substance use and crime, greater accessibility and utilization of treatment services, and stronger institutional capacity in urban settings. In contrast, in rural areas, limited treatment access and weaker reporting coverage may attenuate observable effects. In the Mechanisms section, we further examine whether comprehensive treatment programs (designed to address multiple forms of substance misuse simultaneously) generate consistent reductions across all substance-related crime categories. Such integrated approaches could limit substitution across drugs, helping explain the stronger effects observed in urban settings, where access to both treatment and potential substitutes is greater.

Consistent with this interpretation, we also find that the mitigating effect of SAT facilities on the temperature–crime relationship is stronger in counties with higher educational attainment (columns 3–4, Panel A), higher income levels (columns 5–6, Panel B), and higher labor-force participation rates (columns 7–8, Panel B). These results suggest that communities with greater socioeconomic resources are more able to access, utilize, and benefit from treatment services, and that complementary institutional capacity may enhance the effectiveness of SAT facilities.

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 consequences of substance abuse induced by higher temperatures. 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

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

where we interact county-level daily average temperature $T_{c(i)dmt}$ and total precipitation $P_{c(i)dmt}$ with county-level pre-2010 exposure to prescription opioids ($exposure_{c(i)}$) and an indicator variable which takes value of one for the post-reformulation period, starting from 2010. The remainder of the specification replicates Equation 1, with jurisdiction-calendar day, month-year, jurisdiction-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 relative effect of temperatures between high and low opioid exposure before and after the reformulation, while accounting for annual and state-specific differences in the direct effects of meteorological conditions on crimes and for day-month jurisdiction-specific unobserved heterogeneity.

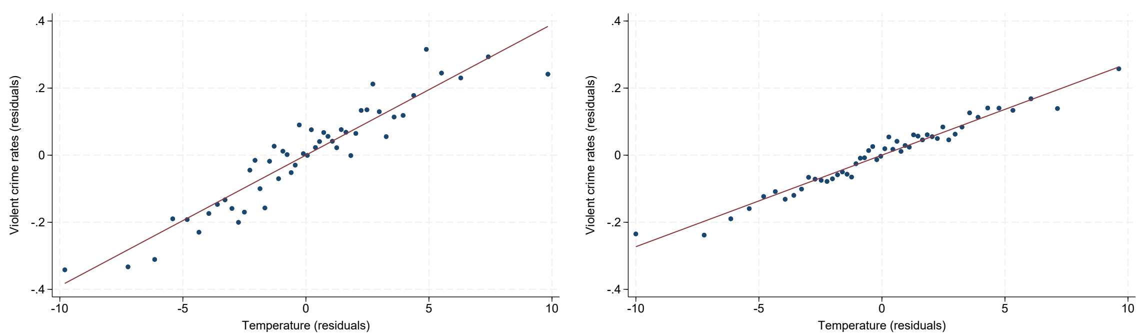
To rule out any potential differential pre-intervention trends between high- and low-exposure counties to prescription opioids and shed light on potential heterogeneous temporal dynamics of the treatment, we also estimate a specification in the form of an event study. First, we allow for temporal heterogeneous effects of the policy by time window after the policy intervention. We interact temperatures and pre-intervention exposure with four dummies that, respectively, take value of one for i) pre-reformulation years (2006 to 2009); ii) years immediately following reformulation (2011-2013); iii) years 2014 to 2016 for medium-run impacts; iv) long-run impacts for several years post-reformulation (2017-2023). Second, we allow for the interaction between daily temperatures and pre-2010 exposure to opioids to vary for each of the 16 years in the sample. 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, the year OxyContin was reformulated.

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-day-month, month-year, jurisdiction-year, and day-of-week 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 triple-difference 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 all violent crime outcomes, including assault, rape, homicide, and intimate partner violence, and for monetary crimes. When we unpack monetary crimes by type, the policy is effective at moderating only temperature-induced robbery cases but not fraud or gambling. Quantitatively, we find that a 1°C increase in 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 triple interaction term 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.

The magnitude is similar when we unpack by category of violent crimes: 11% for assaults, 6% for rapes, and 12% for homicides. When focusing cases of violent crimes (assaults, rapes, and homicides) on female intimate partners (column 3), the magnitude is also similar. 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. This result suggests that policies regulating substance abuse can play a meaningful role in mitigating the social costs of temperature-induced violent behavior.

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 noted in Section 3, opioid misuse may amplify these impulses such as discomfort, stress, and impulsivity induced by higher temperatures prior to reformulation, either by lowering inhibition thresholds or by aggravating withdrawal-related irritability. The 2010 reformulation, by reducing access to abuse-prone opioid formulations, 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 4 and 9 in Table F1) remain largely unaffected and do not differentially respond to higher temperatures in higher opioid exposed counties nor to their reformulation.

Table 2: Effects of opioid reformulation on temperature and crimes

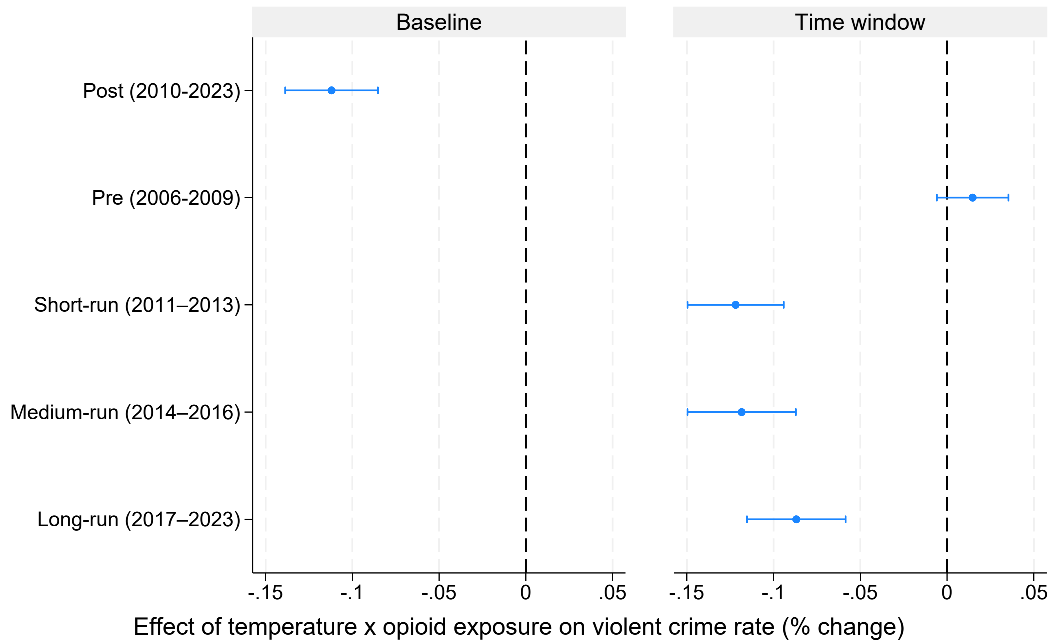
	Cases per 100,000 people			
	Violent crime (1)	Assault (2)	IPV (3)	Fraud (4)
Temperature × Opioid exposure	0.0336***	0.0329***	0.00686***	0.000488
	(0.00420)	(0.00410)	(0.00120)	(0.000963)
Temperature × Opioid exposure × Post-policy	-0.0341***	-0.0334***	-0.00696***	-0.000484
	(0.00414)	(0.00404)	(0.00119)	(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-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓
Day-of-Week 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-policy* 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.

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 consider violent crimes (embedding assaults, rapes, and homicides). 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. On the right-hand side, we explore the temporal dynamics by allowing for 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 (2017-2021) after the policy. 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 that might confound the relationship heterogeneous effects of temperatures on violent crimes by opioid prescription exposure. 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. Figure F1 shows how the policy affects other categories of crime (assaults, intimate partner violence, and frauds) over time. We document similar patterns of the policy that persistently reduces the effect of temperatures in counties with higher exposure to opioids for specific violent crimes, including assaults and violence in intimate contexts; whereas, like in our triple difference baseline estimates, 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.

Figure 8 further unpacks the results and displays the estimates of the triple interaction term—for the same four crimes—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 cases of violence on female intimate partners, decreases in high-exposure counties relative to low-exposure counties. The event study estimates confirm that the effect is persistent over time, and while smaller in magnitude after 2017,

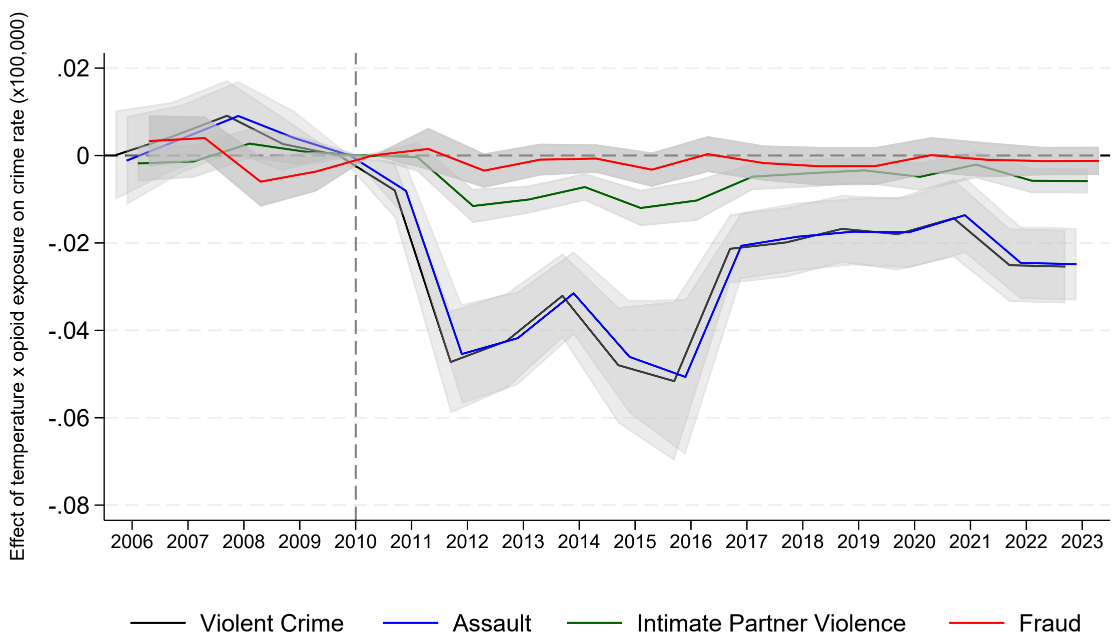
Figure 7: Dynamic effects of opioid reformulation on daily temperature-violent crimes



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 year-specific and state-specific temperature and precipitation, jurisdiction-day-month, month-year, jurisdiction-year, and day-of-week fixed 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 policy is still effective at reducing the impact of temperatures in counties with high exposure to opioid prescriptions. The responsiveness of the temperature-violent crimes relationship decreases in high-exposure resulting in an average relative decrease of 0.03 cases per 100,000 people/1°C/day. The dynamic effect of the policy reveals a notable pattern: significant alterations in the relationship between temperature and crimes emerge more starkly starting 2012, two years after the implementation. A plausible explanation for the delayed efficacy of the policy in reducing temperature sensitivity lies in the potential repercussions of abrupt curbing opioid intake. This cessation may precipitate withdrawal symptoms, spur substitution with substances offering intoxicating effects, and collectively exacerbate dependency while increasing emotional states among individuals in the initial post-policy period.

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 year-specific and state-specific temperature and precipitation, jurisdiction-day-month, month-year, jurisdiction-year, and day-of-week fixed effects. Shaded area represent the 95% confidence intervals with standard errors clustered at the county-level.

Robustness. Our results are robust to a variety of alternative specifications 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 (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). In particular, our robustness exercises involving aggregation and alternative fixed effects suggest that our estimated effects are independent from unobservables controlled for by our fixed effects, allaying concerns on sample selection or other channels, such as temperature affecting crime reporting and police effectiveness, confounding our estimated relationship.

Heterogeneity. As for SAT facilities, we next explore how the mitigating effect of the opioid reformulation on the temperature–violent crime relationship varies across the same socio-economic county characteristics (Table F7).

Population density shapes both the baseline sensitivity of violent crime to temperature and the mechanisms through which opioid misuse interacts with heat-induced aggression. On one hand, higher density may amplify interpersonal frictions and raise the propensity for violent behavior under heat stress. On the other, urban areas offer greater access to illicit opioid substitutes, such as heroin or synthetic opioids (an hypothesis we further examine in Section 6.1), following the reformulation of OxyContin, potentially offsetting the reduction in misuse of prescription opioids. Consistent with this substitution mechanism, we find that the attenuation effect of the policy is stronger in rural counties, where the reformulation reduced misuse more effectively and where the elasticity of violent crime with respect to temperature declined by 28% relative to the pre-policy mean, compared to 0.3% in urban counties (columns 1–2, panel A).

The reformulation also has a larger mitigating effect in counties with below-median college attainment (columns 3–4, panel A). Similarly, the policy is more effective in poorer counties and in those with lower labor force participation (panel B). In these socioeconomically disadvantaged contexts, the reformulation likely reduced misuse more sharply, weakening the channels such as stress, impulsivity, and impaired emotional regulation through which higher temperatures amplify aggression, and thereby attenuating the temperature–violent crime 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 through which substance abuse regulation can moderate temperature-induced violent crimes is by reducing offenses involving substance use. Acknowledging the limitations in measuring substance-involved violent crimes discussed in Section 2.1, we examine whether substance abuse regulation policies mitigate the impact of temperature across our three major categories of violent crimes, filtering by reported cases in which offenders were recorded as using substances.

Panel A of Table 3 shows that the expansion of SAT facilities significantly dampens the temperature–violent crime gradient for substance-related offenses. The largest reductions occur in alcohol-involved cases, consistent with alcohol being the most common reason for treatment admission (about 40%) and with our motivating evidence that alcohol consumption and heat are complements. We also find a smaller but statistically meaningful reduction for marijuana-involved crimes. In contrast, we detect no consistent effects for cocaine- or heroin-related crimes, where estimates are imprecise.

Panel B examines the effect of the OxyContin reformulation. Opioid misuse is often accompanied by complementary substance use (Compton et al., 2021), which can amplify violent behavior during hot days. We find that the reformulation substantially reduced the temperature sensitivity of crimes involving any substance or alcohol, suggesting that limiting access to abusable opioids indirectly may have curbed complementary alcohol use. In contrast, we detect no significant changes for crimes involving cocaine, heroin, or marijuana. While we cannot rule out partial substitution from Oxycontin, our results suggest that the temperature-crime relationship involving these substances did not strengthen following the opioid reformulation.

Results for both policies persist across subcategories of violent crimes—assault (Table F8) and intimate partner violence (Table F9).

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

	Violent crimes 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***	0.00000007	-0.00000024	-0.00000168*
	(0.00002)	(0.00002)	(0.00000025)	(0.00000038)	(0.00000098)
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***	1.25e-6	0.000002	0.00001
	(0.0009)	(0.0008)	(0.000007)	(0.00003)	(0.00004)
Temperature × Opioid exposure × Post-policy	-0.0059***	-0.0057***	-0.000002	0.00001	-0.00006
	(0.0009)	(0.0008)	(0.000007)	(0.00003)	(0.00004)
Pre-policy mean outcome	0.0385	0.0356	0.00001	0.0001	0.0004
Observations	38,033,629	38,033,629	37,301,114	37,301,114	37,301,114

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-day-month, jurisdiction-year, month-year, day-of-week fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-day-month, jurisdiction-year, month-year, day-of-week 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.

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). For this reason, we explore whether the effectiveness of our second policy of interest, the 2010 opioid reformulation, depends on geographic access to these illicit substitutes, using the distance from each county's population centroid to the nearest legal U.S.–Mexico border crossing as a proxy for potential access to trafficked fentanyl-laced products.[9]

We find that the reformulation's effect is significantly stronger in counties farther from the border. The policy reduces the temperature impact on violent crimes by 16.6% in counties above the median distance to the border, compared to just 0.4% in counties below the median (Table 4). Although these results are purely 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 substitutes may attenuate the effectiveness of supply-side opioid policies.

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	0.00703	0.0431***	0.00755	0.0421***	0.00176	0.00689***
	(0.00742)	(0.00665)	(0.00737)	(0.00651)	(0.00196)	(0.00152)
Temperature × Opioid exposure × Post-policy	-0.0187***	-0.0348***	-0.0187***	-0.0340***	-0.00375***	-0.00552***
	(0.00479)	(0.00605)	(0.00485)	(0.00591)	(0.00128)	(0.00158)
Pre-policy mean outcome	4.672	0.209	4.516	0.202	1.119	0.043
Observations	15,660,962	15,665,063	15,660,962	15,665,063	15,660,962	15,665,063

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. Panel A controls for jurisdiction-day-month, jurisdiction-year, month-year, day-of-week fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-day-month, jurisdiction-year, month-year, day-of-week 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 our two substance abuse regulation policies interact with other contemporaneous regulations governing access to other substance. In particular, we examine

[9]Geographic coordinates of U.S.–Mexico border crossings are 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.

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 and treatment effectiveness. Prior work suggests that legal access to medical marijuana may reduce dependence on more dangerous substances and lower opioid addiction and overdose deaths (Powell et al., 2018). If access to medical marijuana favors substitution away from prescription and illicit opioids, we would expect the SAT expansion to be more effective at reducing the temperature-crime gradient in states where medical marijuana is legally available since treatment and substitution channels would reinforce each other. Conversely, the OxyContin reformulation should be more effective in states without medical marijuana laws, where legal substitutes to prescription opioids are not available.

Table 5 provides evidence consistent with these hypotheses. Panel A shows that the mitigating effects of SAT expansion on the temperature sensitivity of violent crimes, assaults, and intimate partner violence are larger in magnitude in states with legal access to medical marijuana (columns 2-4-6). Panel B shows that the OxyContin reformulation reduces the temperature-crime gradient only in states without medical marijuana (columns 1-3-5).[10] When medical marijuana is legally accessible, and thus available as a therapeutic substitute, we do not document a significant effect of opioid reformulation in reducing the crime sensitivity to temperatures. Consistent with this interpretation, the estimated coefficient on the double interaction between temperature and opioid prescriptions is small and statistically indistinguishable from zero in states with medical marijuana laws, but positive and significant where such access is absent. Although associative, these results suggest that access to medical marijuana dampens the substitution to more destructive and uncontrolled substances such as heroin, thereby muting the co-benefits of the opioid reformulation on the effect of temperatures.

[10] We observe similar patterns for other categories of crime (Table F10).

Table 5: Effects of substance abuse regulation policies on temperature-crimes by medical marijuana laws

	Medical Marijuana Law					
	Violent Crime		Assault		Intimate Partner Violence	
	Without	With	Without	With	Without	With
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: SAT facilities						
Temperature × SAT	-0.0003***	-0.0003**	-0.0003***	-0.0003**	-0.00008***	-0.0001*
	(0.00009)	(0.0001)	(0.00008)	(0.0001)	(0.00002)	(0.00005)
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	0.0511***	-0.0117	0.0501***	-0.0114	0.00973***	-0.00364
	(0.00594)	(0.0129)	(0.00581)	(0.0127)	(0.00143)	(0.00370)
Temperature × Opioid exposure × Post-policy	-0.0519***	-0.00590	-0.0508***	-0.00569	-0.00993***	0.0000988
	(0.00581)	(0.00513)	(0.00568)	(0.00519)	(0.00144)	(0.00182)
Pre-policy mean outcome	0.237	5.011	0.230	4.859	0.051	1.295
Observations	21,706,634	5,712,301	21,706,634	5,712,301	21,706,634	5,712,301

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-day-month, jurisdiction-year, month-year, day-of-week fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-day-month, jurisdiction-year, month-year, day-of-week 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.

6.3 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 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 to heat exposure 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 both policies by climate. Table 6 reports results for SAT facilities (Panel A) and for the opioid reformulation (Panel B). In both cases, effects are larger and statistically significant only in counties in the coldest tercile of daily mean temperature. In Panel B, the temperature-opioid exposure 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	-0.00020*	-0.00009	-0.00010	-0.00020*	-0.00008	-0.00010	-0.00004*	-0.00006	-0.00010
	(0.00009)	(0.00010)	(0.00040)	(0.00009)	(0.00010)	(0.00040)	(0.00002)	(0.00005)	(0.00020)
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***	0.0151***	0.00343	0.0332***	0.0148***	0.00331	0.00520**	0.00226*	0.000572
	(0.00881)	(0.00506)	(0.00628)	(0.00857)	(0.00488)	(0.00627)	(0.00214)	(0.00136)	(0.00204)
Temperature × Opioid exposure × Post-policy	-0.0387***	-0.00573	-0.00368	-0.0383***	-0.00577*	-0.00355	-0.00572***	0.0000617	-0.000605
	(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-day-month, jurisdiction-year, month-year, day-of-week fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-day-month, jurisdiction-year, month-year, day-of-week 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 explore whether substance abuse regulation policies mitigate effects of temperatures on crime on specific times of the day. Opioid abuse impairs both sleep duration and quality (Bertz et al., 2019), and increases in nighttime temperatures further reduce sleep quality and increase the likelihood of insufficient sleep (Minor et al., 2022; Obradovich et al., 2017). These combined effects may diminish individuals' ability to cope with stress, increasing the likelihood of aggressive responses to aversive stimuli generated by weather conditions and substance consumption (Rauer and El-Sheikh, 2012). Exploiting intra-daily variation in temperature and using the reported time of crime occurrence, we estimate the effects on crimes committed in the morning, afternoon, evening, and night (Table F11). While we document the policy to be effective in reducing the temperature sensitivity of violent crimes, assaults, and intimate partner violence cases, across all times of day, the effects are largest in the evening and at nights. For example, while the policy reduces the impact of temperatures on violent crimes committed in the mornings and afternoons by respectively 6.9% and 7.5% of the pre-policy average, violent crimes in the evenings and at nights are reduced by 16.5% and 14.9%. These results are consistent with the policies potentially mitigating the sleep-deprivation channel through which substance abuse negative consequences are exacerbated under heat stress.

Day of the week. Because changes in time use (and, potentially, social interactions) 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 test this hypothesis by comparing the association between crimes and temperatures on weekdays and weekends. 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 F12).

Characteristics of crime. We also examine if the policies are more effective at mitigating certain categories of crimes by characteristics, including whether violent crimes involved a firearm or based on the location of the crime. Our estimates suggest that SAT facilities were significantly more effective at reducing violent crimes and assault outside, whereas for intimate partner violence the mitigating effect is indoor environments and at home (Table E7). For Oxycontin reformulation, we instead find no statistically significant difference between the effect of the policy at mitigating the impact of temperatures on violent crimes, assaults, and intimate partner violence cases involving a firearm (Table F13).

7 Monetizing social benefits of the policies in a changing climate

Our estimates suggest that policies targeting substance abuse can generate ancillary social benefits by moderating the sensitivity of violent crimes to temperature. Yet, these welfare gains have been omitted from any prior cost–benefit analyses of substance-abuse policies. From a climate adaptation perspective, omitting these co-benefits may lead to an incomplete evaluation of policy effectiveness and an underestimation of the net social returns to policy interventions that indirectly mitigate climate impacts (Carleton et al., 2024). The natural question, therefore, is whether the implied benefits are economically meaningful and how they compare to alternative policies in terms of cost-effectiveness.

To conduct our exercise, we choose the case of intimate partner violence, one of the most prevalent violent crimes in the United States (approximately 18% of all violent offenses), which entails substantial social costs, estimated at $3.6 trillion, largely due to lifetime health and productivity losses.[11]

We use our baseline estimates to monetize the net social benefit of the opioid reformulation policy on the temperature–IPV relationship. We compute the aggregate willingness to pay for the OxyContin reformulation to reduce the risk of temperature-driven intimate partner violence, and we compare it to benefits from other policy interventions.

We estimate that, on average, after OxyContin reformulation a 1°C increase is associated with 260,968 fewer cases of IPV on females. Using the lifetime cost of an intimate partner violence of $135,556 (in $2023) from Peterson et al. (2018), we estimate that in U.S.a person would pay $117 (in $2023) the Oxycontin reformulation to reduce temperature-

[11] In Appendix C we provide additional details on the relationship between temperature and intimate partner violence.

driven IPV. On aggregate, this willingness to pay amounts to approximately \$35 billion (in \$2023).[12]

This expected social benefit is economically meaningful. To illustrate, the estimated welfare gain is equivalent to the social return from the establishment of about 3909 SAT facilities (Bondurant et al., 2018).[13], and it is also comparable to the creation of roughly 67,057 new mental healthcare facilities (Deza et al., 2022).[14] Moreover, the estimated benefit offsets the fiscal costs of key U.S. federal programs addressing opioid abuse and domestic violence, such as the funding for the Comprehensive Addiction and Recovery Act (CARA),[15] the annual budget for the Violence Against Women Act (VAWA),[16] and the funding allocation to the Family Violence Prevention and Services Act (FVPSA).[17] Finally, it is an order of magnitude larger than Colmer and Doleac (2023)'s estimate of the aggregate willingness to pay to reduce the risk of temperature-driven homicides—\$3.380 billion/1°C.

Overall, this back-of-the-envelope calculation underscores the substantial welfare gains from addressing substance abuse as a means of mitigating the adverse effects of rising temperatures on violent crime.

[12] This is obtained as follows: (0.00686 - 0.00696) IPV cases per 100,000 people / 100,000 $\times$ 365 (days) $\times$ Average total population between 2006-2009 $\times$ Avg. opioid prescriptions per person between 2006-2009) $\times$ \$135,556 (lifetime cost of an IPV case) $\times$ 1 (degree Celsius change in temperature).

[13] Bondurant et al. (2018) estimates that the social benefit associated with the opening of a Substance Abuse Treatment facility is \$9.04 million (in \$2023).

[14] Deza et al. (2022) estimate that opening an additional mental healthcare facility would be associated with a \$0.527 million (in \$2023) reduction in crime costs.

[15] 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. More information can be found here.

[16] The Violence Against Women Act, approved in 1994 and reauthorized in 2022, provides about \$3.28 billion (in \$2023) to create and support comprehensive, cost-effective responses to domestic violence, sexual assault, dating violence and stalking. More information can be found here.

[17] The Coronavirus Aid, Relief, and Economic Security (CARES) Act included \$52.99 million (in \$2023) of supplemental funding to address DV under the 1984 Family Violence Prevention and Services Act Program. More information can be found here.

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 examine how two major interventions aimed at reducing substance abuse—the expansion of substance abuse treatment (SAT) facilities and the reformulation of OxyContin—shape the temperature–violent crime gradient.

Our findings reveal a consistent pattern. First, increases in daily temperature are significantly associated with more violent crimes, particularly in counties with greater exposure to substance misuse. Second, both policies substantially attenuate this temperature sensitivity. The opening of an additional SAT facility per 100,000 residents reduces the effect of temperature on violent crime by roughly one-quarter, with particularly pronounced effects for assault and intimate partner violence. These mitigating effects are strongest in urban and socioeconomically advantaged counties, where treatment access and institutional capacity are greater. Third, the OxyContin reformulation fully offsets the amplified temperature response observed in high-opioid-exposure counties, effectively eliminating the differential sensitivity to heat. Event-study estimates of the OxyContin reformulation indicate that these moderating effects are persistent over time.

Together, these results highlight that efforts to reduce substance abuse can yield ancillary adaptation benefits by dampening environmentally driven aggression. To our knowledge, these welfare gains have never been incorporated into cost–benefit assessments of substance-abuse or climate policies. Yet our back-of-the-envelope calculations suggest that the social benefits from the reformulation policy alone are economically meaningful, comparable in size to large-scale violence-prevention and public-health investments.

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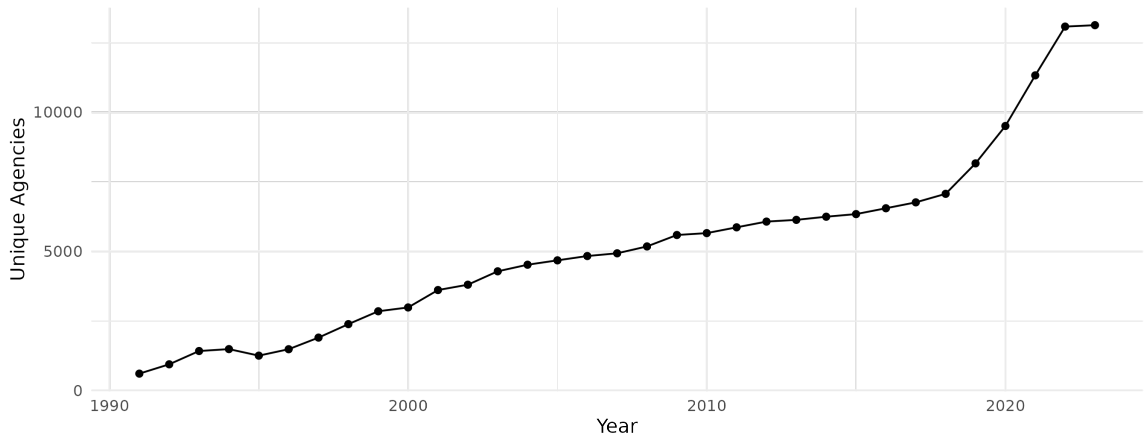
Appendix

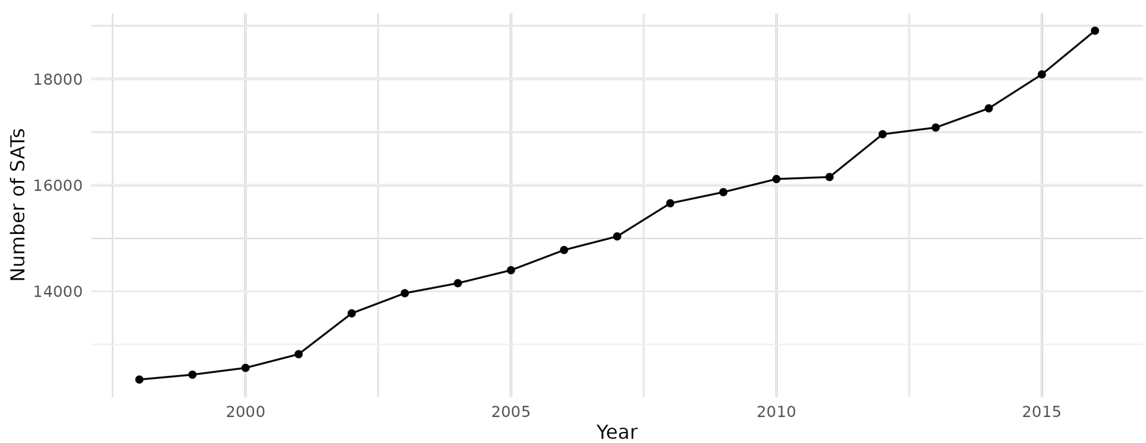
A Additional figures

Figure A1: Number of reporting jurisdictions, 1991-2023



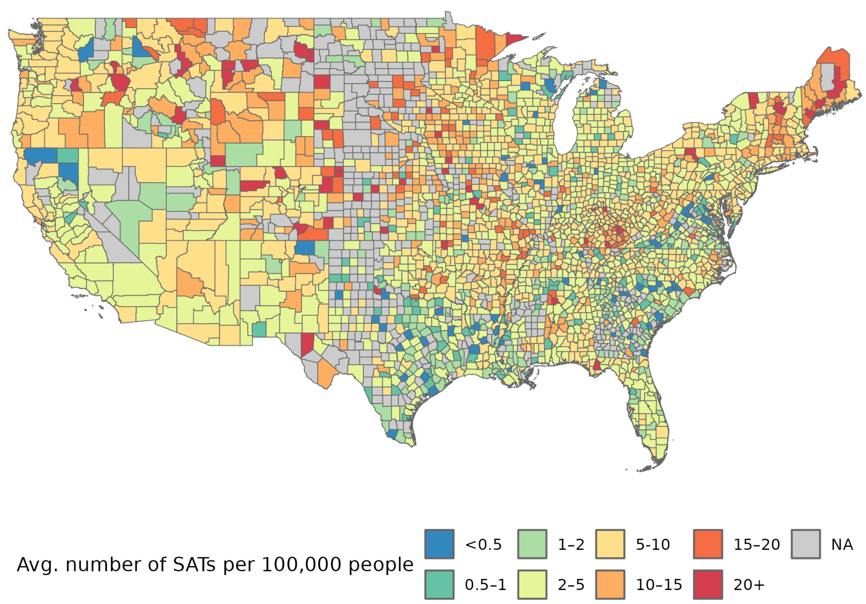
Notes: Figure shows the number of reporting agencies (ORIs) in the NIBRS data set by year.

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



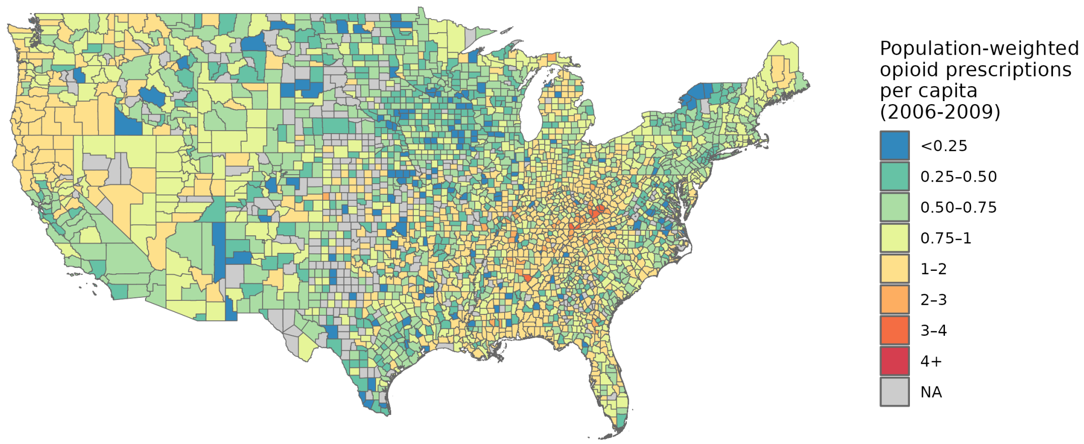
Notes: Figure shows the number of opened substance abuse treatment facilities in the CBS data set by year.

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 final estimation sample. Sample mean is 0.85, standard deviation is 0.46.

B Temperature and crime

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

$$Y_{idmy} = f(T_{c(i)dmy}, P_{c(i)dmy}) + \mu_{idm} + \phi_{my} + \delta_{dw} + \varepsilon_{idmy} \tag{B.1}$$

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_{idm} are jurisdiction-day-month fixed effects; ϕ_{my} and δ_{dw} are respectively month-of-year and day-of-week fixed effects. We cluster standard errors at the county-level and estimate Equation B.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 B2); excluding agencies that do not report for all twelve months (Table B3); clustering standard errors at the state level (Table B4); estimating without applying survey weights (Table B5); and polynomials of weather variables up to the fourth degree (Table B6). When computing non-linear transformations in temperature and precipitation, we perform them at the grid-cell level before weighing and averaging, in order to preserve non-linearities in the original weather data (Hsiang, 2016).

In Appendix Table B1 we also report the coefficients on precipitation, where we find that is significantly 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.

Table B1: The relationship between temperature and crime (1991-2023)

	Cases 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***	0.0016***	0.0015***	0.0000331***	0.00000597***	0.0004***	0.0019***	0.0000521**
	(0.0015)	(0.0005)	(0.0005)	(0.0000120)	(0.00000213)	(0.0001)	(0.0006)	(0.0000249)
Precipitation (m)	-0.1727**	-0.0921***	-0.0906***	-0.0014	-0.0004	-0.0130**	0.0052	-0.0024
	(0.0671)	(0.0279)	(0.0270)	(0.0014)	(0.0003)	(0.0056)	(0.0221)	(0.0071)
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-Day-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-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 B2: Relationship between temperature and crime (Accounting for Covid-19)

	Crime	Violent	Assault	Rape	Homicide	IPV female	Monetary	Fraud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Excluding COVID-19 period (post 2019)								
Temperature (°C)	0.0062**	0.0019**	0.0019**	0.0000397*	0.0000058*	0.0004**	0.0027*	0.0000843
	(0.0031)	(0.0010)	(0.0009)	(0.0000240)	(0.00000302)	(0.0002)	(0.0014)	(0.0000600)
Precipitation (m)	-0.3001*	-0.1300**	-0.1284**	-0.0016	-0.0002	-0.0169*	-0.0372	-0.0121
	(0.1607)	(0.0609)	(0.0605)	(0.0017)	(0.0004)	(0.0098)	(0.0386)	(0.0139)
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. Including COVID dummy								
Temperature (°C)	0.0047***	0.0016***	0.0015***	3.21e-05***	5.92e-06***	0.0004***	0.0019***	5.24e-05**
	(0.0015)	(0.0005)	(0.0005)	(1.23e-05)	(2.09e-06)	(0.0001)	(0.0006)	(2.63e-05)
Precipitation (m)	-0.1797***	-0.0941***	-0.0917***	-0.0022	-0.0005	-0.0138**	0.0015	-0.0043
	(0.0623)	(0.0286)	(0.0277)	(0.0014)	(0.0003)	(0.0058)	(0.0225)	(0.0060)
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-Day-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-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 excludes 2020 and 2021. Panel B includes a dummy from 2020 onward. 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 B3: The relationship between temperature and crime (12-month reporting agencies)

	Crime	Violent	Assault	Rape	Homicide	IPV female	Monetary	Fraud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature (°C)	0.0075**	0.0025**	0.0025**	0.0000446**	0.00000947**	0.0006**	0.0031**	0.0000683*
	(0.0033)	(0.0011)	(0.0011)	(0.0000225)	(0.00000444)	(0.0003)	(0.0014)	(0.0000412)
Precipitation (m)	-0.2056***	-0.1454**	-0.1419**	-0.0032	-0.0008	-0.0260**	0.0617	0.0038
	(0.0751)	(0.0582)	(0.0564)	(0.0024)	(0.0005)	(0.0128)	(0.0672)	(0.0086)
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-Day-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-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 B4: 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**	0.0016**	0.0015**	0.0000321**	0.00000593**	0.0004**	0.0019**	0.0000524
	(0.0018)	(0.0006)	(0.0006)	(0.0000154)	(0.00000235)	(0.0001)	(0.0007)	(0.0000413)
Precipitation (m)	-0.1797**	-0.0941***	-0.0917**	-0.0022	-0.0005*	-0.0138**	0.0014	-0.0044
	(0.0697)	(0.0344)	(0.0342)	(0.0015)	(0.0002)	(0.0065)	(0.0278)	(0.0069)
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-Day-Month FE FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-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 B5: The relationship between temperature and crime (Unweighted)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Temperature (°C)	0.0871***	0.0250***	0.0244***	0.0006***	0.0000730***	0.0056***	0.0331***	0.0013***
	(0.0022)	(0.0010)	(0.0010)	(0.0000716)	(0.0000215)	(0.0002)	(0.0014)	(0.0004)
Precipitation (m)	-1.600	-1.210***	-1.124**	-0.0756*	-0.0121	-0.0210	1.130	-0.0139
	(2.140)	(0.4522)	(0.4658)	(0.0404)	(0.0109)	(0.1885)	(1.743)	(0.1334)
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-Day-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-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 B6: The relationship between temperature and crime (4th Polynomial)

	Crime (1)	Violent (2)	Assault (3)	Rape (4)	Homicide (5)	IPV female (6)	Monetary (7)	Fraud (8)
Temperature (°C)	0.0068**	0.0014**	0.0014**	0.00004*	0.0000064**	0.0002**	0.0032**	0.0001**
	(0.0031)	(0.0007)	(0.0006)	(0.00002)	(0.0000030)	(0.0001)	(0.0014)	(0.000062)
Temperature^2	-0.0000492	0.0000302***	0.0000297***	0.00000046	0.000000054	0.00000949***	-0.0000402	-0.00000438
	(0.0000658)	(0.00000925)	(0.00000898)	(0.000000545)	(0.0000000516)	(0.00000247)	(0.0000354)	(0.00000342)
Temperature^3	-0.00000366	-0.000000275	-0.000000232	-0.000000043	-0.00000000312	0.00000000887	-0.00000189	-0.0000000972
	(0.00000314)	(0.000000615)	(0.000000597)	(0.0000000288)	(0.00000000354)	(0.0000000957)	(0.00000149)	(0.0000000992)
Temperature^4	0.0000000575	-0.0000000189	-0.0000000193	0.000000000432	0.0000000000202	-0.00000000408*	0.0000000375	0.00000000404
	(0.0000000927)	(0.0000000145)	(0.0000000138)	(0.000000000956)	(0.0000000000942)	(0.00000000236)	(0.0000000463)	(0.00000000391)
Precipitation (m)	-1.138***	-0.3760***	-0.3616***	-0.0131**	-0.0022	-0.0309	-0.2119	0.0047
	(0.3378)	(0.1284)	(0.1263)	(0.0061)	(0.0019)	(0.0273)	(0.1498)	(0.0350)
Precipitation^2	42.95***	16.75***	16.02***	0.6617	0.1025	1.024	4.633	-1.915
	(14.93)	(6.012)	(5.927)	(0.4563)	(0.1512)	(1.608)	(9.402)	(2.303)
Precipitation^3	-447.2**	-220.9**	-209.0**	-10.99	-0.9968	0.1380	9.488	57.30
	(215.7)	(91.60)	(90.10)	(10.51)	(3.588)	(28.04)	(159.7)	(42.57)
Precipitation^4	840.7	613.6	559.2	54.46	-2.469	-137.2	-273.4	-406.1*
	(921.2)	(389.2)	(384.8)	(70.01)	(24.56)	(151.0)	(796.2)	(235.7)
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-Day-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-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.

C 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).

Understanding the drivers of intimate partner violence is a major priority, although the factors affecting these crimes are complex. Prior work has focused on 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.

D Temperature and substance abuse: Survey evidence

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 econometric specifications

SAT direct effect. Our baseline model do not allow to identify both a direct effect of SAT availability and an interaction term capturing how the temperature–crime elasticity varies with treatment access, due to the inclusion of jurisdiction-year fixed effects. We can relax our specification to leverage that variation to identify the direct effect of opening an additional SAT facility. Our specification looks as follows:

$$\begin{aligned} Y_{idmt} = \quad & \alpha\, SAT_{c(i)t-1} + \beta_1\, T_{c(i)dmt} \times SAT_{c(i)t-1} + \beta_2\, T_{c(i)dmt} + \\ & \gamma_1\, P_{c(i)dmt} \times SAT_{c(i)t-1} + \gamma_2\, P_{c(i)dmt} + \\ & + \mu_{idm} + \lambda_{mt} + \varepsilon_{idmt} \end{aligned} \tag{B.2}$$

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 still exploit within-county, within-year daily variation in temperature and precipitation around those average exposure levels.

More restrictive framework. Finally, we estimate two more restrictive specifications. We first augment Equation 1 by replacing day-of-week and month–year fixed effects with date fixed effects, κ_{dmt}:

$$\begin{aligned} Y_{idmt} = \quad & \beta\, T_{c(i)dmt} \times SAT_{c(i)t-1} + \gamma\, P_{c(i)dmt} \times SAT_{c(i)t-1} + \\ & + \delta_{c(i)} T_{c(i)dmt} + \theta_{c(i)} P_{c(i)dmt} + \delta_t T_{c(i)dmt} + \theta_t P_{c(i)dmt} + \\ & + \mu_{idm} + \phi_{it} + \kappa_{dmt} + \varepsilon_{idmt} \end{aligned} \tag{B.3}$$

This specification absorbs all national daily shocks—such as major events or holidays—that could affect crime patterns across jurisdictions on the same date. Second, We next replace jurisdiction fixed effects with jurisdiction–month–year fixed effects, μ_{imt}, and include week-of-year and day-of-week fixed effects:

$$
\begin{aligned}
Y_{idmt} = \quad & \beta_1\, T_{c(i)dmt} \times SAT_{c(i)t-1} + \gamma_1\, P_{c(i)dmt} \times SAT_{c(i)t-1} + \\
& + \delta_{c(i)} T_{c(i)dmt} + \theta_{c(i)} P_{c(i)dmt} + \delta_t T_{c(i)dmt} + \theta_t P_{c(i)dmt} + \\
& + \mu_{imt} + \lambda_{wt} + \kappa_{dw} + \varepsilon_{idmt}
\end{aligned}
\tag{B.4}
$$

Here, μ_{imt} (jurisdiction $\times$ month $\times$ year) absorb all slow-moving and seasonal components within each jurisdiction–year, such as long-term crime trends or local policing patterns. Identification thus comes from day-to-day fluctuations in temperature within each jurisdiction–month–year cell. λ_{wt} (week-of-year) and κ_{dw} (day-of-week) further account for systematic national temporal patterns in crime reporting.

Again, in all specifications we weigh our regressions using the average population in the jurisdiction during the sample period, and we cluster standard errors at the county-level.

E.2 Additional figures and tables

Table E1: The mitigating effect of substance-abuse treatment facilities

	Cases per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT	-0.0004***	-0.0004***	-0.0000874***	-0.0000349
	(0.0000723)	(0.0000704)	(0.0000196)	(0.0000251)
Precipitation × SAT	-0.1066**	-0.1042**	-0.0693***	0.0151
	(0.0463)	(0.0455)	(0.0245)	(0.0230)
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	26,879,916	26,879,916	26,879,916	26,879,916
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-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 E2: The mitigating effect of substance-abuse treatment facilities (Including never treated)

	Cases per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT	-0.0004***	-0.0004***	-0.0000828***	-0.0000335
	(0.0000703)	(0.0000685)	(0.0000192)	(0.0000245)
Precipitation × SAT	-0.1085**	-0.1059**	-0.0743***	0.0146
	(0.0458)	(0.0451)	(0.0244)	(0.0223)
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	30,245,622	30,245,622	30,245,622	30,245,622
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-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 E3: The mitigating effect of substance-abuse treatment facilities (12-month reporting agencies)

	Cases per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT	-0.0005***	-0.0005***	-0.0001***	-0.0000408
	(0.0000730)	(0.0000711)	(0.0000209)	(0.0000267)
Precipitation × SAT	-0.0695	-0.0717	-0.0534**	-0.0030
	(0.0509)	(0.0500)	(0.0258)	(0.0248)
Mean Outcome	3.2315	3.1192	0.8679	0.4941
Observations	23,628,071	23,628,071	23,628,071	23,628,071
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-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 E4: The mitigating effect of substance-abuse treatment facilities (First opening)

	Cases per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Temperature × SAT (first opening)	0.0018	0.0018	0.0008	-0.0005
	(0.0015)	(0.0015)	(0.0005)	(0.0006)
Precipitation × SAT (first opening)	-1.832	-1.886	-0.4801	-1.306*
	(1.456)	(1.441)	(0.7490)	(0.7923)
Mean Outcome	0.4443	0.4288	0.1193	0.0673
Observations	26,879,916	26,879,916	26,879,916	26,879,916
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-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 E5: The mitigating effect of substance-abuse treatment facilities (Alternative fixed effects)

	Cases per 100,000 people			
	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)
Panel A: Juri-Day-Month + 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
Precipitation	-1.401	-1.392	-0.2197	0.0579
	(0.9307)	(0.9127)	(0.1504)	(0.0501)
Temperature × SAT	-0.0009**	-0.0009**	-0.0002**	-0.0000931**
	(0.0004)	(0.0003)	(0.000077)	(0.0000405)
Precipitation × SAT	0.1011	0.1004	0.0148	-0.0033
	(0.0652)	(0.0638)	(0.0099)	(0.0043)
Panel B: Juri-Day-Month + Juri-Year + Date				
Temperature	0.0289***	0.0281***	0.0066***	0.0015***
	(0.0014)	(0.0014)	(0.0004)	(0.0003)
Precipitation	-2.345***	-2.328***	-0.1825	-0.0127
	(0.2602)	(0.2566)	(0.1163)	(0.1283)
Temperature × SAT	-0.0013***	-0.0013***	-0.0003***	-0.0000784***
	(0.0000973)	(0.0000947)	(0.0000218)	(0.0000201)
Precipitation × SAT	0.1413***	0.1363***	-0.0009	0.0278**
	(0.0288)	(0.0285)	(0.0115)	(0.0124)
Panel C: Juri-Month-Year + Day-of-Week + Week-of-Year + Temp/Prcp × Year/County				
Temperature × SAT	-0.0008***	-0.0008***	-0.0002***	-0.0000374
	(0.0001)	(0.0001)	(0.0000397)	(0.0000340)
Precipitation × SAT	-0.0859**	-0.0846**	-0.0632***	0.0012
	(0.0426)	(0.0411)	(0.0216)	(0.0206)
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 E6: Heterogeneous effects of substance-abuse treatment facilities on temperature-violent crime on county characteristics

	Violent crimes per 100,000 people			
	Urban/Rural		College Education Level	
	Urban	Rural	Below median	Above median
	(1)	(2)	(3)	(4)
Panel A: Urbanization and Education				
Temperature × SAT	-0.0007***	-0.0002	-0.00009	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.00009)
Mean Outcome	0.133	2.875	3.288	0.230
Observations	9,824,844	17,048,132	9,214,059	17,651,612
	Income		Labor Force Participation	
	Below median	Above median	Below median	Above median
	(5)	(6)	(7)	(8)
Panel B: Economic Stress				
Temperature × SAT	-0.0001	-0.0004***	-0.0002	-0.0004***
	(0.0001)	(0.00009)	(0.0001)	(0.00009)
Mean Outcome	3.548	0.231	3.550	0.136
Observations	10,119,924	16,759,992	17,552,235	13,773,790
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-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 E7: Heterogeneous effects of substance-abuse treatment facilities on temperature-violent crime by location

	Cases per 100,000 people			
	Indoor	Outdoor	Home	Outside
	(1)	(2)	(3)	(4)
Panel A: Violent Crimes				
Temperature × SAT	-3.64e-05	-8.47e-05***	-0.0002***	-8.32e-05**
	(5.13e-05)	(9.59e-06)	(4.38e-05)	(3.54e-05)
Precipitation × SAT	-0.1151***	0.0038	-0.1318***	-0.0255
	(0.0415)	(0.0092)	(0.0360)	(0.0259)
Mean Outcome	0.347	0.020	0.286	0.128
Panel B: Assault				
Temperature × SAT	-2.67e-05	-8.23e-05***	-0.0002***	-8.22e-05**
	(5.00e-05)	(9.32e-06)	(4.26e-05)	(3.51e-05)
Precipitation × SAT	-0.1145***	0.0033	-0.1321***	-0.0230
	(0.0412)	(0.0090)	(0.0358)	(0.0253)
Mean Outcome	0.334	0.020	0.275	0.125
Panel C: Intimate Partner Violence				
Temperature × SAT	-7.91e-05***	-4e-06	-7.93e-05***	1.21e-08
	(1.71e-05)	(2.51e-06)	(1.66e-05)	(6.02e-06)
Precipitation × SAT	-0.0868***	0.0002	-0.0859***	-0.0162*
	(0.0232)	(0.0039)	(0.0225)	(0.0087)
Mean Outcome	0.105	0.003	0.100	0.016
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-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

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 E8: 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	-0.0003***	-0.0005***	-0.0003***	-0.0005***	-0.00007***	-0.0001***
	(0.00008)	(0.0001)	(0.00008)	(0.0001)	(0.00002)	(0.00004)
Precipitation × SAT	0.0455	-0.1317	0.0462	-0.1248	-0.0134	-0.0070
	(0.0596)	(0.1139)	(0.0587)	(0.1140)	(0.0278)	(0.0560)
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-Day-Month FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓	✓	✓
Month-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.

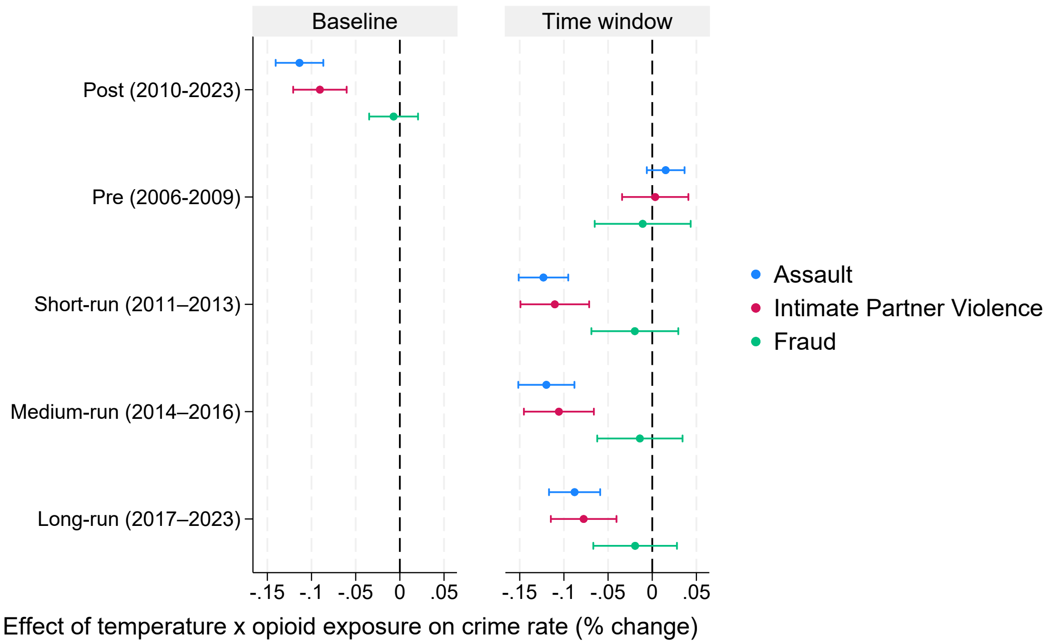
F Opioid reformulation: Additional results and robustness

Table F1: Effects of opioid reformulation on temperature and crimes

	Cases 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	0.0336***	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-policy	-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-Day-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓	✓

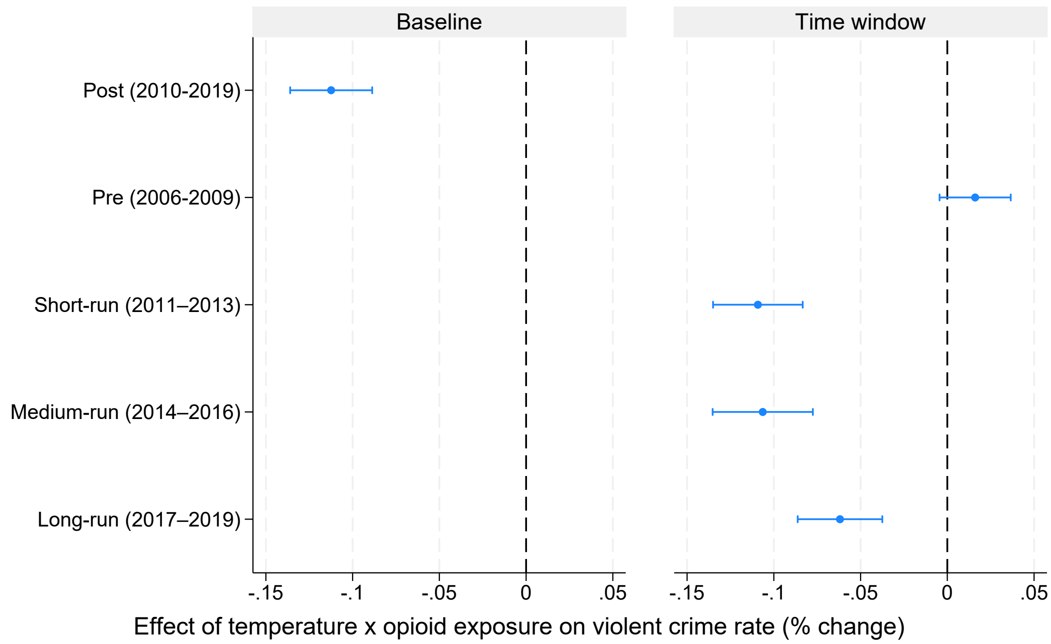
Notes: The dependent variable is the number of crimes per 100,000 people. *Post-policy* is a dummy variable equal to 1 for the post-reformulation period, starting from 2010. *Opioid exposure* is the county-level pre-2010 exposure to opioids. Standard errors are clustered at the county level. All regressions 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



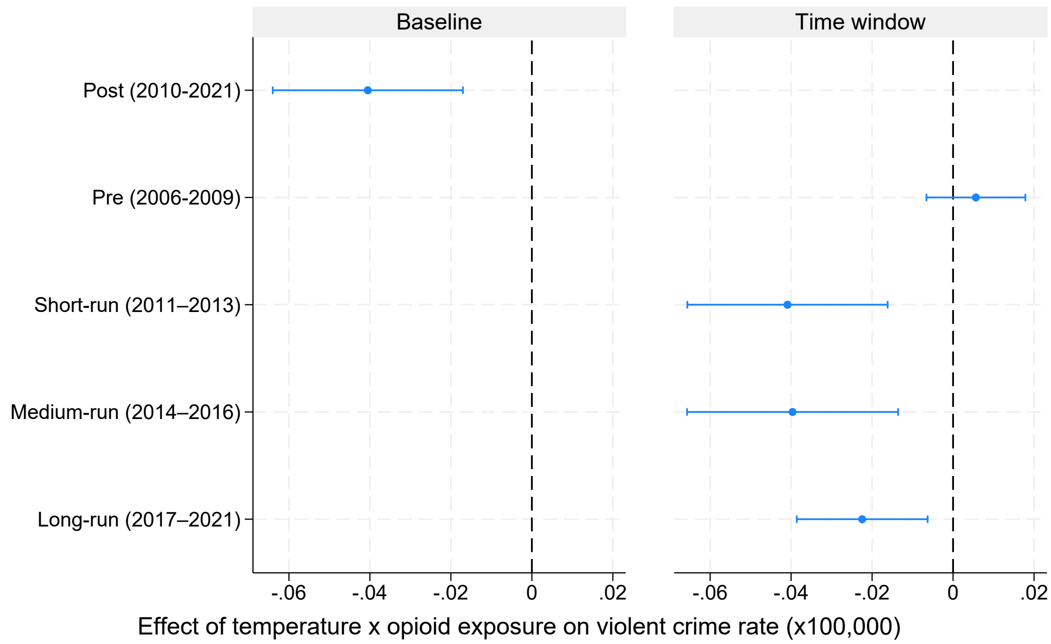
Notes: Each panel and color corresponds to a separate regression. The dependent variable is the daily charge rate per 100,000 inhabitants, normalized on the y-axis according to the average charge rate of each category before 2010. The figure plots the coefficients of the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opiod 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 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 opiod 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 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 opiod prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation years, 2010-2021, 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 2017-2021, several years post-reformulation. The regression also controls for year-specific temperature and precipitation, jurisdiction-day, jurisdiction-month-year, week-of-year and day-of-week fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the state-level.

Table F2: Baseline 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-policy	-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				✓	✓	✓
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: Baseline 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***	0.0304***	0.0335***	0.0307***
	(0.00472)	(0.00419)	(0.00446)	(0.00385)
Temperature × Opioid exposure × Post-policy	-0.0411***	-0.0309***	-0.0341***	-0.0311***
	(0.00468)	(0.00414)	(0.00440)	(0.00378)
Pre-policy mean outcome	0.315	0.300	0.298	0.305
Panel B: Assaults				
Temperature × Opioid exposure	0.0390***	0.0298***	0.0330***	0.0304***
	(0.00459)	(0.00406)	(0.00437)	(0.00378)
Temperature × Opioid exposure × Post-policy	-0.0396***	-0.0303***	-0.0335***	-0.0308***
	(0.00455)	(0.00400)	(0.00431)	(0.00372)
Pre-policy mean outcome	0.304	0.290	0.288	0.294
Panel C: Intimate Partner Violence				
Temperature × Opioid exposure	0.00862***	0.00586***	0.00652***	0.00672***
	(0.00146)	(0.00134)	(0.00121)	(0.00114)
Temperature × Opioid exposure × Post-policy	-0.00877***	-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-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-of-Year FE	✓	✓	✓	✓
Day-of-Week 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-crimes with opioid exposure using pills and shipments

	Pills				Shipments			
	Violent Crimes	Assault	IPV	Fraud	Violent Crimes	Assault	IPV	Fraud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature × Opioid exposure	0.0004***	0.0004***	$6 \times 10^{-5*}$	-6.87×10^{-6}	0.3034***	0.2969***	0.0525***	0.0044
	(0.0001)	(0.0001)	(3.54×10^{-5})	(2.21×10^{-5})	(0.0614)	(0.0603)	(0.0151)	(0.0107)
Temperature × Opioid exposure × Post-policy	-0.0005***	-0.0005***	$-7.47 \times 10^{-5***}$	8.06×10^{-6}	-0.4054***	-0.3955***	-0.0698***	-0.0053
	(9.9×10^{-5})	(9.76×10^{-5})	(2.57×10^{-5})	(2.29×10^{-5})	(0.0458)	(0.0450)	(0.0115)	(0.0109)
Jurisdiction-Day-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-of-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-Week fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓
Pre-policy mean outcome	0.3525	0.3415	0.0774	0.0684	0.3525	0.3415	0.0774	0.0684
Observations	32,249,414	32,249,414	32,249,414	32,249,414	32,249,414	32,249,414	32,249,414	32,249,414

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. *Post* is a dummy variable equal to 1 for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to opioids. In columns 1 and 2 *Exposure* is measured as county-specific 2006-2009 average opioid pills and shipments per capita from the ARCOS database, respectively. 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

	Violent Crimes	Assault	Intimate Partner Violence	Fraud
	(1)	(2)	(3)	(4)
Temperature × Opioid exposure	0.0331***	0.0324***	0.0052***	0.0009
	(0.0055)	(0.0054)	(0.0014)	(0.0011)
Temperature × Opioid exposure × Post-policy	-0.0315***	-0.0306***	-0.0050***	-0.0012
	(0.0039)	(0.0038)	(0.0010)	(0.0011)
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Pre-policy mean outcome	0.4545	0.4402	0.0997	0.0884
Observations	27,738,246	27,738,246	27,738,246	27,738,246

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 using alternative fixed effects

	Violent Crimes (1)	Assault (2)	IPV (3)	Fraud (4)
Temperature × Opioid exposure	0.0340***	0.0335***	0.00602***	-0.000992
	(0.00519)	(0.00509)	(0.00130)	(0.00101)
Temperature × Opioid exposure × Post-policy	-0.0371***	-0.0365***	-0.00674***	0.00149
	(0.00425)	(0.00419)	(0.00110)	(0.00101)
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
Temperature-State	✓	✓	✓	✓
Precipitation-State	✓	✓	✓	✓
Temperature-Year	✓	✓	✓	✓
Precipitation-Year	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Observations	31,326,025	31,326,025	31,326,025	31,326,025

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 F7: Heterogeneous effects of opioid reformulation on temperature-crimes by county characteristics

	Violent crimes per 100,000 people			
	Urban/Rural		College Education Level	
	Urban	Rural	Below median	Above median
	(1)	(2)	(3)	(4)
Panel A: Urbanization and Education				
Temperature × Opioid exposure	0.0228**	0.0282***	0.0303***	0.0232**
	(0.00949)	(0.00409)	(0.00571)	(0.0109)
Temperature × Opioid exposure × Post-policy	-0.0154**	-0.0308***	-0.0401***	-0.0192*
	(0.00623)	(0.00425)	(0.00482)	(0.0100)
Observations	10,920,860	20,405,165	2,907,511	17,603,255
Pre-policy mean outcome	4.852	0.110	0.320	2.716
	Income		Labor Force Participation	
	Below median	Above median	Below median	Above median
	(5)	(6)	(7)	(8)
Panel B: Economic Stress				
Temperature × Opioid exposure	0.0451***	0.00702*	0.0280***	0.0393***
	(0.00903)	(0.00390)	(0.00628)	(0.00830)
Temperature × Opioid exposure × Post-policy	-0.0500***	-0.00158	-0.0349***	-0.0359***
	(0.00804)	(0.00354)	(0.00461)	(0.00809)
Observations	18,851,739	12,471,728	17,552,235	13,773,790
Pre-policy mean outcome	0.257	5.174	0.233	3.678
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

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 F8: 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***	0.000002	-0.00001	0.0001
	(0.0008)	(0.0008)	(0.00001)	(0.00003)	(0.00004)
Temperature × Opioid exposure × Post-policy	-0.0057***	-0.0056***	-0.000002	0.00001	-0.0001
	(0.0008)	(0.0008)	(0.00001)	(0.00003)	(0.00004)
Pre-policy mean outcome	0.0372	0.0344	0.00001	0.0001	0.0004
Observations	38,033,629	38,033,629	37,301,114	37,301,114	37,301,114

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-day-month, jurisdiction-year, month-year, day-of-week fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-day-month, jurisdiction-year, month-year, day-of-week 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 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***	-0.000001	-0.000003	0.000001
	(0.0004)	(0.0004)	(0.000001)	(0.00001)	(0.00003)
Temperature × Opioid exposure × Post-policy	-0.0021***	-0.0021***	0.000001	0.000003	-0.0000002
	(0.0004)	(0.0004)	(0.000002)	(0.00001)	(0.00003)
Pre-policy mean outcome	0.0143	0.0134	0.00000	0.00003	0.0001
Observations	38,033,629	38,033,629	37,301,114	37,301,114	37,301,114

Notes: Table reports on 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-day-month, jurisdiction-year, month-year, day-of-week fixed effects and county- and year-specific temperature and precipitation effects. Panel B controls for jurisdiction-day-month, jurisdiction-year, month-year, day-of-week 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 F10: 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	0.000859***	-0.00000995	0.000130	-0.000188
	(0.000323)	(0.000578)	(0.0000860)	(0.000147)
Temperature × Opioid exposure × Post-policy	-0.000883***	-0.000229	-0.000192**	-0.00000420 ***
	(0.000333)	(0.000723)	(0.0000865)	(0.000155)
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Observations	21,706,634	5,712,301	21,706,634	5,712,301
Pre-policy mean outcome	0.006	0.138	0.001	0.014

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 F11: 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	0.00357***	0.00703***	0.0172***	0.00891***
	(0.00103)	(0.00122)	(0.00249)	(0.00144)
Temperature × Opioid exposure × Post-policy	-0.00357***	-0.00745***	-0.0197***	-0.0106***
	(0.00108)	(0.00108)	(0.00208)	(0.00117)
Pre-policy mean outcome	0.052	0.099	0.119	0.071
Panel B: Assaults				
Temperature × Opioid exposure	0.00351***	0.00704***	0.0172***	0.00844***
	(0.00101)	(0.00123)	(0.00244)	(0.00140)
Temperature × Opioid exposure × Post-policy	-0.00351***	-0.00751***	-0.0196***	-0.00998***
	(0.00106)	(0.00110)	(0.00205)	(0.00115)
Pre-policy mean outcome	0.051	0.096	0.117	0.068
Panel C: Intimate Partner Violence				
Temperature × Opioid exposure	0.000508**	0.00102***	0.00281***	0.00206***
	(0.000252)	(0.000393)	(0.000540)	(0.000464)
Temperature × Opioid exposure × Post-policy	-0.000506**	-0.00110***	-0.00339***	-0.00248***
	(0.000255)	(0.000367)	(0.000484)	(0.000398)
Pre-policy mean outcome	0.012	0.018	0.028	0.018
Jurisdiction-Day-Month FE	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Temperature × Year	✓	✓	✓	✓
Temperature × State	✓	✓	✓	✓
Precipitation × Year	✓	✓	✓	✓
Precipitation × State	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓
Observations	31,326,025	31,326,025	31,326,025	31,326,025

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 F12: 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	0.0314***	0.0444***	0.0307***	0.0437***	0.00610***	0.0121***
	(0.00416)	(0.00525)	(0.00408)	(0.00510)	(0.00118)	(0.00181)
Temperature × Opioid exposure × Post-policy	-0.0319***	-0.0451***	-0.0311***	-0.0443***	-0.00618***	-0.0123***
	(0.00410)	(0.00518)	(0.00402)	(0.00504)	(0.00116)	(0.00180)
Jurisdiction-Day-Month FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week 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: 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 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 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 F13: 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***	0.0172***	0.0033***	0.0200***
	(0.0031)	(0.0004)	(0.0018)	(0.0024)	(0.0005)	(0.0029)
Temperature × Opioid exposure × Post-policy	-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***	0.0167***	0.0032***	0.0196***
	(0.0030)	(0.0004)	(0.0018)	(0.0023)	(0.0005)	(0.0028)
Temperature × Opioid exposure × Post-policy	-0.0259***	-0.0010***	-0.0131***	-0.0169***	-0.0033***	-0.0199***
	(0.0030)	(0.0004)	(0.0018)	(0.0023)	(0.0005)	(0.0028)
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)	(8.64×10^{-5})	(0.0003)	(0.0009)	(0.0001)	(0.0010)
Temperature × Opioid exposure × Post-policy	-0.0062***	-0.0001	-0.0012***	-0.0054***	-0.0002	-0.0057***
	(0.0010)	(8.64×10^{-5})	(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-Day-Month FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Year FE	✓	✓	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week 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: Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.