Co-benefits of Substance Abuse Regulation on Temperature and Intimate Partner Violence

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Abstract

Intimate Partner Violence (IPV) is a critical public health concern often linked to substance abuse. Environmental factors can exacerbate substance addiction and use, potentially leading to increased violence. Building on prior work showing that higher temperatures increase violent behavior, we investigate whether substance abuse regulations affect the relationship between temperature and IPV. Leveraging administrative data combined with random fluctuations in daily temperature the jurisdiction level in the United States, we document that an exogenous abuse-deterrent reformulation of opioids in 2010 significantly attenuates the temperature-IPV relationship in counties with higher initial rates of prescription opioid usage. Our main mechanism suggests an indirect reduction in the complementary use of other substances, particularly alcohol, during hot days. Our findings indicate that policies targeting substance abuse may have co-benefits in mitigating the adverse effects of temperature increases.

Keywords: Intimate Partner Violence; Temperature; Opioid; Substance Abuse; Alcohol

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

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1 Introduction

In the United States, 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 IPV are complex. An extensive body of research has established a link between higher temperature and violent behavior through physiological and psychological mechanisms. Previous research has documented this pattern in the US for criminal activity (Ranson, 2014; Heilmann et al., 2021), homicides (Colmer and Doleac, 2023) and child maltreatment (Evans et al., 2023). An often cited primary risk factor associated with IPV perpetration is substance abuse, which can induce individuals to become aggressive and can intensify impulse control disorders (Angelucci and Heath, 2020; Schilbach, 2019). In particular, opioid misuse has been associated with IPV (Stone and Rothman, 2019; Radcliffe et al., 2021; Pryor et al., 2021). Supply-side shocks that restrict access to addictive substances, including prescription opioids, can thus either exacerbate or mitigate violent behavior (Dave et al., 2023; Evans et al., 2022).

In this paper, we examine whether higher temperatures affect IPV perpetration in the United States, and if a policy originally designed to curtail prescription opioid misuse has unintended consequences on the temperature-IPV relationship. We leverage plausibly exogenous variation in daily temperatures to examine their effect on IPV rates at the jurisdiction-level. We combine this variation with a policy intervention in 2010 that reformulated the main legal opioid, OxyContin. This unexpected supply-side intervention addressed the overprescription of opioids to mitigate their addictive risks. We design an empirical approach close to a triple-difference exploiting two sources of county-level variation, where the triple interaction term of temperature, pre-intervention opioid exposure, and post-policy time indicator identifies the moderating role of supply-side shock reducing opioid availability, under the assumption that the temperature-IPV relationship would have stayed the same had the reformulation not occurred.

Using administrative data from the FBI's National Incident-Based Reporting System (NIBRS) from 1991 to 2021, we find a strong positive effect of average daily temperature on IPV cases. On average, a one-degree Celsius increase in temperature is associated with 0.0058 more daily cases of IPV per 100,000 people, a 0.87% increase compared to the mean. The effect is more pronounced for nonfatal aggressive behaviours, during evening and night, when the offender is under the influence of alcohol and marijuana, and in urban, poorer, and warmer counties. Critically, the impact of temperature also increases as the county-level exposure to opioids increases, suggesting a compounding effect of opioid use disorders and environmental factors.

Combining daily temperature variation with county-level variation in exposure to prescription opioids, the triple-difference estimates reveal that a 1°C increase is associated with 0.0127 fewer IPV cases per 100,000 people after the opioid reformulation, mitigating on average 94% of temperature-driven IPV in the period 2006-2021. The event-study analysis documents that the attenuating role of the policy persists over ten years. Altogether these results suggest positive unintended co-benefits of the opioid reformulation in mitigating the positive effect of temperature on intimate partner violence.

We examine several potential mechanisms through which the reformulation of OxyContin mitigates the impact of temperature on IPV. First, we observe two key findings: a reduction in alcohol-related temperature-driven IPV due to the policy, and that temperature increases heavy drinking especially in counties more exposed to opioids. This suggests that the reformulation, targeting opioid users, has reduced the co-(ab)use of alcohol consumption during hot days. Second, our findings indicate that the policy's effectiveness is muted in areas with access to alternative substances like marijuana and fentanyl. Specifically, we find no mitigation effect in states with legal access to medical marijuana or in areas closer to the Mexican border where (illegal) fentanyl may serve as a substitute. Third, we find evidence that the opioid reformulation was more effective at attenuating the temperature-IPV relationship in areas with more substance abuse treatment facilities, suggesting that a supportive infrastructure may enhance the impact of the reformulation. Fourth, our analysis demonstrates that the policy's impact is consistent across different times of day, indicating a broad effect on crime patterns irrespective of the temporal context. Finally, we find no evidence to suggest that the policy operates through changes in social interactions.

Our findings contribute to a burgeoning 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 (Ranson, 2014; Baylis, 2020; Heilmann et al., 2021; Mukherjee and Sanders, 2021; Behrer and Bolotnyy, 2022). Our contribution stands in examining the impact of temperature on a specific and widespread type of violent behavior, namely intimate partner violence. We do so at a highly granular spatial and temporal resolution, exploiting daily variation in temperature from hourly information at the jurisdiction-level, holding jurisdiction-month-year, week-of-year and day-of-week factors fixed.

Our results on the role of the policy environment contribute to the growing literature on the unintended consequences of policies in mediating climate impacts on socio-economic outcomes.[1] These studies focus on health care access attenuating the temperature-mortality relationship (Mullins and White, 2020; Cohen and Dechezleprêtre, 2022), public employment (Fetzer, 2020; Garg et al., 2020; Banerjee and Maharaj, 2020), and cash transfers programs (Adhvaryu et al., 2024; Baysan et al., 2019; Garg et al., 2020; Christian et al., 2019) reducing climate sensitivity of violent behavior and learning. More restrictive gun laws attenuate the temperature-homicide relationship (Colmer and Doleac, 2023). Our study sheds light on the positive externalities of a supply-side intervention in opioid availability as a mediator to the temperature-IPV relationship.

Our paper also contributes to the literature that studies the determinants of IPV perpetration. Previous 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 gap (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. (2023) document that the opioid reformulation significantly reduced IPV exposure for women, but induced a notable uptick in heroin-involved IPV. We explore environmental factors as measured by daily temperature as a new determinant, and provide novel

[1] Policies can also have negative externalities. For instance, the highly subsidized federal crop insurance program makes US farmers more sensitive to extreme heat as a result of moral hazard (Annan and Schlenker, 2015).

evidence on the mediating role of the opioid reformulation and examine the mechanisms behind the interplay between temperature and opioid disorder use.

Finally, we speak to the literature on the opioid epidemic which has pervaded the United States in the past decades (Arteaga and Barone, 2022; Dave et al., 2023; Evans et al., 2019). Evans et al. (2022) document that the reformulation of OxyContin and the implementation of must-access prescription drug monitoring programs increase child physical abuse and neglect. Gihleb et al. (2022) document higher entry into foster care in states with the must-access Prescription Drug Monitoring Programs (PDMPs). Arteaga and Barone (2023) find greater exposure to the opioid epidemic continuously increased the Republican vote share. In this paper, we document the positive externality of the supply-side intervention on opioid availability on the temperature-IPV relationship.

2 Background and Data

2.1 Potential physiological mechanisms

The primary channels through which increase in temperatures could affect violent behavior are physiological and psychological effects on impulse controls and aggression (Anderson, 2001). Higher temperatures can deteriorate mental health, increasing anxiety, despair and isolation (Mullins and White, 2019). These factors can in turn exacerbate substance use (Martins et al., 2012; Gros et al., 2013). Recent studies address the "looming confrontation between the world's complex overdose crisis and its equally intensifying climate emergency" (Ezell, 2023), documenting that vulnerabilities associated with opioid use disorders are exacerbated by changes in climate, leading to more opioid-related emergency department visits and hospitalisations due to increases in temperature (Chang et al., 2023; Parks et al., 2023). We complement these previous findings with monthly state-level evidence of a positive association between temperature and non-fatal opioid-related emergency department visits (Appendix Figure A1).

Primarily, several prescription drugs, including opioids, have been associated with increases in criminal behavior and violence towards others (Moore et al., 2010; Sim, 2023), and, in particular, towards intimate partners (Moore et al., 2011). Moreover, often opioid abuse co-moves with alcohol consumption (Esser et al., 2019, 2021), which is one of the main channels for increases in criminal behavior (Anderson et al., 2018) and domestic violence (Klostermann and Fals-Stewart, 2006).[2] Complementarily, epidemiological literature has long been interested in the relationship between opioid misuse and IPV, highlighting the bi-directionality of the association, with higher prevalence of opioid use in IPV victims and perpetrators and higher prevalence of IPV among those who use opioids (see Stone and Rothman (2019) for an extensive review).

Altogether, there is suggestive evidence of potential interactions between opioids abuse, temperature, and intimate partner violence. Disruptions to opioid access induced by supply-side shocks such as the 2010 OxyContin reformulation that we study in this paper may have an ambiguous effect on the relationship between temperature and intimate partner violence. On the one hand, reduced opioid access may favor substitution into other illicit drugs, inducing increases in violent behavior. On the other hand, supply-side interventions could reduce crime through the reduction of opioid abuse and of the overall pool of addicts (Havens et al., 2014). Which of the two mechanisms prevails is an empirical question that we address in this paper.

[2] In this regard, Cohen and Gonzalez (2024) find that 9% of weather-induced crimes are triggered by an additional use of alcohol determined by weather conditions.

2.2 Data

We briefly summarize the data (with complementary information provided in the Appendix). First, we retrieve administrative comprehensive data on reported cases of intimate partner violence at the finest temporal and geographical scale (Section 2.2.1). Second, we combine these data with granular weather data to identify the effect of temperature (Section 2.2.2). Third, we employ information on the prescriptions of opioids to test the mediating role of the policy intervention (Section 2.2.3). Last, we combine the resulting data set with a number of additional information at various resolution (individual-, county-, and state-level) to explore mechanisms and channels of the relationship between temperature and intimate partner violence incidence.

2.2.1 Intimate Partner Violence Cases

We use data from the FBI's National Incident-Based Reporting System (NIBRS) from 1991 to 2021, which contains reports of IPV cases to individual law enforcement agencies (*ORIs*, or jurisdictions) including information on the characteristics of the victim (e.g. age, gender), the offender (e.g. gender and relationship to the victim), and the incident date. We construct daily reports of IPV cases at the jurisdiction level (Dave et al., 2023). We include aggravated assaults, simple assaults, forced sex, and intimidation, experience by female victims, from relationships that consist of spouses, common-law spouses, boyfriends/girlfriends, homosexual partners, ex-spouses, and ex-boyfriends/girlfriends. Our primary dependent variable is the number of IPV cases per 100,000 people.[3]

[3] We obtain the daily rate of IPV incidents scaling by population at the jurisdiction-level from (1) the ICPSR website at the University of Michigan and (2) 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 IPV cases as a dependent variable.

Unfortunately, our data also come with drawbacks. First, the number of agencies reporting data in the NIBRS is increasing over time, ranging from 609 in 1991 to 11,384 in 2021. Moreover, departments drop in and out of the sample over time, leading to an unbalanced panel. To attenuate this issue, we construct a panel at the jurisdiction-day level that is balanced at the year level, and we exploit within-year variation to obtain our estimates.[4]

Second, NIBRS are not representative of the whole United States, as only a self-selected sample of agencies report their crime. Nonetheless, despite this geographic coverage gaps, the NIBRS data are considered to be the most consistent and comparable national data available on daily crime rates in the US (DOJ, 2018) and have been widely used in previous work (Card and Dahl, 2011; Burkhardt et al., 2019; Jones, 2022; Colmer and Doleac, 2023).

2.2.2 Weather

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 for the representative individual in the county.[5] Although the IPV data are originally at the jurisdiction level, geographical coordinates are not available at

[4]Using the NIBRS data, Colmer and Doleac (2023) construct the panel in a similar way. However, they exclude agencies that did not report 12 months of data for that year to the reporting system since their empirical analysis exploits within-year-month changes in concealed carry laws through a staggered design. In our study, we use a pre- and post-treatment policy design, and, thus, we can relax their data restrictions.

[5]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, as common in climate econometrics (Hsiang, 2016).

the jurisdiction level. Therefore, we match jurisdictions to counties and we exploit these variables for the main analysis. We prefer ERA-5 Land weather data over PRISM Climate Group (PRISM, 2024) - another common weather data source for studies in the US (Colmer and Doleac, 2023; Molitor et al., 2023) - to exploit the finer original temporal resolution of the data (hourly) to compute weather conditions over specific times of the day.

2.2.3 Opioid use and policy background

We study a policy that exogenously curtailed access to opioids as a potential moderating or exacerbating factor to the temperature-IPV relationship. Since the 1990s, opioid prescriptions in the United States escalated quickly from 76 million to more than 250 million (Volkow et al., 2014). OxyContin, released by Purdue Pharma, was one of the main catalyst of such an opioid epidemic. OxyContin contained oxycodone - a narcotic analgesic - and was originally used to treat moderate to severe chronic pain. Nevertheless, it also had high risk for addiction and dependence, with an extensive number of people across the United States that started abusing it. To address the opioid crisis and reduce the misuse of OxyContin, Purdue Pharma developed an abuse deterrent version of the drug, making it more difficult to crush or dissolve. The version was approved by the Food and Drug Administration in April 2010, and became effective in August 2010 with the new formulation being distributed and the previous formulation being discontinued without any public notice (Evans et al., 2019).

The reformulation led to a decrease in OxyContin abuse (Cicero and Ellis, 2015; Sessler et al., 2014). Nevertheless, it emerged a substitution pattern away from OxyContin to other illicit opioids such as heroin and synthetics, documented by an increase in overdoses related to these drugs in the post-reformulation period

(Powell and Pacula, 2021). Recent studies document an increase in child physical abuse and neglect after OxyContin's reformulation (Evans et al., 2022) and heroin-involved IPV (Dave et al., 2023).

We exploit the national reformulation of OxyContin in 2010 as a result of an unanticipated, unilateral decision from the producers, Purdue Pharmaceutical. To obtain a measure of pre-intervention exposure to opioid prescription, we use the population-weighted mean number of all Schedule II opioid prescriptions per capita for the period 2006 to 2009 from the Centers for Disease Control (CDC). This measure accounts for a broader set of prescription opioids than the intervention which was only targeting OxyContin, but it allows for more granular geographical variation at the county-level than previous studies exploiting state-level variation (Alpert et al., 2022). Appendix Figure A2 shows the spatial distribution of exposure to prescription opioids prior to the reformulation.

We also gather county-level data on opioid shipments to retail pharmacies from DEA's Automation of Reports and Consolidated Orders System (ARCOS). We compute the average number of opioid pills distributed and of shipments per capita of all Schedule II opioids for the period 2006 to 2009. We use these two alternative measures of opioid exposure to test for the robustness of our policy analysis.

2.2.4 Additional data

In additional analysis, we set out to better understand the mechanisms. We use auxiliary data for this purpose, which we briefly summarize here.

Medical marijuana laws. We explore the substitution/complementary role of legal marijuana on access restrictions to opioids. Legal marijuana reduces opioid addiction and overdose deaths (Powell et al., 2018). We use information at the state-level with medical marijuana access in place (Evans et al., 2022) to study if its availability as a therapeutic substitute can mediate or exacerbate the differential effects of OxyContin's reformulation on the temperature-IPV relationship. If legal access to medical marijuana favors substitution away from opioids, we should observe the opioid reformulation to be effective on attenuating the temperature effect only in states without medical marijuana laws.

Substance-abuse treatment facilities. We also study the complementary role of other policies aimed at reducing abuse and misuse of substances. Particularly, we focus on substance-abuse treatment (SAT) facilities. The existing literature suggests that SATs are an effective measure to reduce drug use, substance-related mortality, and crime as well (Mitchell et al., 2012; Prendergast et al., 2017; Swensen, 2015; Bondurant et al., 2018). We gather the number of open substance-abuse treatment facilities at the county-level using data from the U.S. Census Bureau's County Business Patterns (CBP) for the years 2006-2016 (Bondurant et al., 2018; Swensen, 2015). The CBP reports the annual number of SAT facilities in each county. However, it only includes county with at least one open SAT.[6] For our auxiliary analysis we then construct two variables: (1) a yearly binary variable if in a county there is at least one open SAT facility; (2) a dummy variable indicating whether the county-level number of open SAT establishments is above the median average number of SAT facilities in the period 2006-2016. If the number of SAT clinics in a county is a relevant complementary policy, we expect the effect of OxyContin's reformulation on the temperature-IPV relationship to be greater in counties with open facilities, and where the number of establishments is larger.

Alcohol consumption. To test the role of alcohol consumption as potential mechanism for our analysis, we collect information from the Behavioral Risk Factor Surveillance System (BRFSS) survey. The BRFSS serves as an annual health-related

[6]From 2017 onwards CBP only reports counties with three or more SAT facilities. For this reason in the analysis with SAT we exclude the period 2017-2021.

telephone survey of individuals within the United States, comprising one of the world's largest continuously conducted health survey systems. It includes information on whether a person has drink in the last month, and how many drinks. Moreover, it also provides socio-economic and demographic characteristics of the interviewed individuals. We obtain data for the period 1991-2012 that we merge with ERA5-Land meteorological information.[7] We so construct a repeated cross-section data set with more than 4 million observations.

Socio-demographic covariates. We combine the data set with a plethora of socio-demographic covariates at the county-level. We include the percentage of the county population living in rural areas from the 2010 Census Bureau (Evans et al., 2022). We use two measures to define rich and poor counties, respectively the median household income and the share of population in poverty from the Economic Research Service at the US Department of Agriculture. We obtain county-level population by age, gender and ethnicity groups from the 2010 US Census Bureau, Population Division.[8]

2.3 Descriptive Statistics

Our final combined dataset includes 11,176 jurisdictions (in 1,635 counties) across the United States, for a total of 44,170,732 unique jurisdiction-day observations. Table 1 provides summary statistics on the main variables of interest. On average, in our sample period 0.057 daily cases of IPV per 100,000 are reported. This rate is greater in the period before OxyContin reformulation, and slightly smaller after the policy. Moreover, the average rate also increases as we move from low-opioid

[7]We stop at 2012 as the variable indicating the county of residence is not available in more recent survey waves.

[8]Rural/Urban divide data are available here. Data on income and poverty are available here. Age/gender/ethnicity data are available here.

exposed counties (0.026) to high-opioid exposed counties (1.195). Using data from Centers for Disease Control (CDC), the population-weighted mean number of all Schedule II opioid prescriptions per capita for the period 2006 to 2009 is centered at 0.648 and 1.102 for low- and high-opioid exposed counties, respectively. As for weather variables, in the whole sample daily average temperature and daily total precipitation are 11.092 °C and 0.003 metres.

Table 1: Descriptive Statistics

	1991-2021		1991-2009		2006-2009				2010-2021	
	Mean	SD	Mean	SD	Mean		SD		Mean	SD
					Low	High	Low	High		
NBRIS										
IPV on female per 100,000 people	0.057	0.590	0.076	0.717	0.026	1.195	0.393	2.456	0.049	0.511
CDC										
Per capita opioid prescriptions					0.648	1.075	0.029	0.342		
ERA5-Land										
Average daily temperature (°C)	11.092	10.496	9.465	10.129	9.512	12.421	9.898	10.258	11.879	10.579
Total daily precipitation (m)	0.003	0.007	0.003	0.007	0.003	0.003	0.008	0.007	0.003	0.007
Observations	44,170,732		17,744,918		6,022,651				25,303,374	

Notes: Descriptive statistics are weighted by jurisdiction-location population. "High" ("Low") indicates counties with population-weighted mean per capita opioid prescriptions above (at or below) the sample median of 0.833.

3 Temperature and Intimate Partner Violence

This section examines the impact of temperature on intimate partner violence (IPV) on females. First, we analyse the base relationship between daily temperature realizations and jurisdiction reports of IPV per 100,000 people. Next, we test the heterogeneity of the relationship across socio-demographic characteristics, climatic areas, and opioid exposure. We conclude providing robustness tests for our empirical analysis.

3.1 Econometric Framework

We model the relationship between temperature and intimate partner violence as follows:

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

where Y_{idmy} is the number of reported cases of intimate partner violence on female per 100,000 by jurisdiction i in day d of month m and year y; μ_{imy} are jurisdiction-month-year fixed effects; ϕ_{wy} and δ_{dw} are respectively week-of-year and day-of-week fixed effects. We cluster standard errors at the county-level and estimate Equation 1 with population weights at the jurisdiction level.[9]

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:

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

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 also test for alternative specifications, where we account for potential non-linearities in the relationship between temperature and IPV.

3.2 Results

Table 2 reports the results from the estimation of Equation 1. In Column 1, we exploit month-year and state-month-year variation to identify the relationship temperature-

[9] We also show results without regression weights, since they may lead to less precise estimates, as common with data that represent group-level averages (Solon et al., 2015).

intimate partner violence exposure by females. We estimate that, on average, a 1°C increase in average daily temperature is associated with an increase by 0.0061 more cases of intimate partner violence per 100,000 people, corresponding to a 0.91% increase with respect to the mean. The effect of precipitation is not robust to the inclusion of state-month-year fixed effects.

Columns 2-3 replace state-month-year variation with, respectively, jurisdiction and jurisdiction-month-year fixed effects. As a result, we absorb much more variation in the relationship between intimate partner violence and temperature. We find that, on average, a 1°C increase in average daily temperature is associated with 0.0040-0.0058 more cases of intimate partner violence per 100,000 people, a 0.60%-0.87% increase compared to the mean.

Finally, in column 4 we present the results of our preferred specification. We estimate an identical specification to column 5, but we weight the regression using jurisdiction-location population weights. Adding weights reduces the precision of the estimate. However, the magnitude of the temperature coefficient remains identical to the unweighted estimate. We find that, on average, that a 1°C increase in average daily temperature is associated with 0.0005 more cases of intimate partner violence per 100,000 people. This corresponds to a 0.87% increase compared to the weighted average.

Our estimates align in direction and magnitude with previous work on the relationship between temperature and crimes in the United States. Ranson (2014) shows that the temperature-violent crime relationship is approximately linear. He finds that an additional day between 90 and 99 °F ($\approx$ between 32 and 35 °C) is associated with an increase by 0.6%, 0.9%, 0.7% and 0.4% in murder, rape, aggravated and simple assault cases respectively. Colmer and Doleac (2023) estimates that a 1°C is associated with an increase between 0.8 and 5.7% in the mean murder rate, depending on the specification.

Robustness. Our baseline results are robust to various tests, including excluding (or controlling for) the Covid-19 period (Appendix Table A1); trimming the sample (Appendix Table A2); expressing the dependent variable as count variable (Appendix Table A3); testing alternative fixed-effects (Appendix Table A4), and standard errors clustered at the state level (Appendix Table A5). We also explore non-linear specifications of temperature, using 5-degree temperature bins (Appendix Figure A3, Appendix Table A6), share of hours in a day in a temperature bin (Appendix Table A7), and a up to 4-degree polynomial (Appendix Table A8). The estimates suggest that a linear specification is a good approximation. We also use lags and leads to control for potential displacements of intimate partner violence cases, and anticipatory behaviours (Appendix Table A9). We observe displacement effects offsetting nearly 60 percent of the contemporaneous effect after 21 days.[10] Finally, we also restrict our attention to temperatures over night to examine whether sleep deprivation could be a mechanism behind our baseline findings. We document a similar result in magnitude to our baseline estimates, suggesting that nighttime temperature might be a crucial driver of the relationship (Appendix Table A10). We set out to further explore this mechanism in Section 5.

3.3 Heterogeneous effects of temperature

We explore heterogeneous effects of temperature on intimate partner violence across several dimensions, providing additional insights on the relationship between temperature and intimate partner violence, and the potential mechanisms taking place.

[10] As Cohen and Gonzalez (2024), we find no impact of leads, except for the first lead for temperature. This correlation most likely is due to the correlation during night between the average temperature on day d and the average temperature on day $d-1$.

Table 2: Temperature and Intimate Partner Violence

	Female Intimate Partner Violence per 100,000 people			
	(1)	(2)	(3)	(4)
Temperature (°C)	0.0061***	0.0040***	0.0058***	0.0005**
	(0.0010)	(0.0002)	(0.0003)	(0.0002)
Precipitation (m)	0.2444	-0.3329*	-0.0228	-0.0126
	(0.2413)	(0.1892)	(0.2150)	(0.0102)
Observations	44,170,732	44,170,732	44,170,732	44,170,732
Mean Outcome	0.6697	0.6697	0.6697	0.0574
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
State-Month-Year FE	✓			
Jurisdiction FE		✓		
Jurisdiction-Month-Year FE			✓	✓
Jurisdiction-Location Population Weights				✓

Notes: The dependent variable is the number of intimate partner violence on females 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). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Offenses. First, we test whether temperature only affects specific offenses within the IPV domain. Appendix Table A11 presents our estimates for three different crimes: assault, rape, and murder. Our results suggest that the effect is mainly driven by aggressive behaviours, assault and rape, that do not end up with a murder. Moreover, Appendix Table A12 also highlights that temperature mostly affects crime where firearms are not involved. We find that, on average, a 1°C increase in average daily temperature is associated with 0.0004 more non-firearms cases of intimate partner violence per 100,000 people, a 0.81% increase compared to the mean; whereas, this association falls to 0.00000844 additional cases, a 0.08% increase compared to the mean, when firearms are involved.

Location of the crime. We then examine whether temperature-induced intimate partner violence cases mostly occur inside the home or in other locations. Appendix Table A13 suggests that, even though most IPV offenses occur in the residence (86%), the effect of temperature is not statistically different across locations. We estimate that, on average, a 1°C increase in average daily temperature is associated with 0.0004 cases of intimate partner violence per 100,000 people at home, a 0.92% increase compared to the mean, and 0.0001 cases in other location, a 0.86% increase compared to the mean. Interestingly, the effect of precipitation is negative and significant when we focus on the 'Other' location cases. Rainy days might change people's movement patterns in a way that increases the social interaction with the partner, and so the risk of intimate partner violence.

Time of the day. We further estimate the temperature-IPV relationship based on the time of the crime. We count the number of IPV cases during the morning (6:00am to 11:59am), afternoon (12:00pm to 5:59pm), evening (6:00pm to 11:59pm), and night (12:00am to 5:59am). Appendix Table A14 reports our results. Our findings reveal that the temperature-IPV relationship is stronger between 6:00pm and 6:00am, when 60% of the IPV offenses occur. During the evening, on average, a 1°C increase in average daily temperature is associated with 0.0002 cases of intimate partner violence per 100,000 people, a 0.96% increase compared to the mean. These results show that heat in the day can have a lasting impact on IPV committed during nighttime.

Alcohol and drugs-involving cases. Heat might either increase the abuse of substances like alcohol or physiologically accentuate the effect of these on the human body. In Table A15, we report the impact of temperature on intimate partner violence, based on whether the offender was under the influence of substances, including alcohol, heroin, marijuana, cocaine, and other drugs. Daily average temperature is positively associated with alcohol- and marijuana-related cases of intimate partner violence, while the effect of heroin- and cocaine-IPV offenses is very small and not significant. Analogous evidence in Mexico shows that 9% of weather-related crimes are triggered by an additional use of alcohol determined by weather conditions (Cohen and Gonzalez, 2024).

Levels of opioid prescriptions. In this regard, to add on previous literature that documents a positive association between warmer temperature and opioid abuse (Chang et al., 2023; Parks et al., 2023), we explore whether the effect of temperature on IPV varies by opioid prescriptions per capita (Appendix Table A16). Appendix Figure A4 reports the marginal effect of temperature on IPV cases on females interacted with the population-weighted rate of OxyContin misuse prior to the reformulation. We document a positive effect, i.e., higher temperature increases IPV in counties with higher opioid abuse, suggesting a compounding effect of environmental factors and opioid use disorders. The heterogeneous effect of temperature across opioid exposure remain consistent even when we interact with the opioid exposure variables constructed from the ARCOS database (Appendix Table A17).

County-level socio-demographic characteristics. Finally, we test for the presence of heterogeneous effects across county-level socio-demographic characteristics.[11] Appendix Table A18 reports the estimates for each socio-demographic dimension. First, in column 1 we test the urban-rural divide, defining a jurisdiction

[11] To do so, we allow the temperature-intimate partner violence relationship to vary cross-sectionally across each group (Carleton et al., 2022). We estimate the following regression:

$$Y_{aidmy} = f_a(T_{c(i)dmy}, P_{c(i)dmy}) + \mu_{aimy} + \phi_{wy} + \delta_{dw} + \varepsilon_{aidmy}$$

where $f(T_{c(i)dmy}, P_{c(i)dmy})$ is interacted with a categorical (or dummy) variable for the group of interest a, and γ_{aidy} are group-jurisdiction-month-year fixed effects. The model does not include uninteracted terms for the group a because collinear with γ_{aidy}.

as urban if it is within a county whose urban population share is above the median population-weighted urban share in the sample. Consistent with prior findings (Cohen and Gonzalez, 2024), our estimates indicate that the effect of temperature is more pronounced in urban areas. This might be explained through different factors, such as urban heat island or changes in social interactions during hot days.[12]

Second, we test for heterogeneous distributional effects of temperature on IPV on females. If the costs of temperature are unequally distributed, this could exacerbate inequalities among counties. In columns 2 and 3 we interact average daily temperature with a dichotomous variable indicating above median poverty rate and income level counties. Similarly to Heilmann et al. (2021), we find that counties with above median poverty rate and below income level drive the relationship. To illustrate it, on average, a one-degree Celsius increase in average daily temperature is associated with 0.0015 (0.0020) more cases of intimate partner violence per 100,000 people for above (below) median poverty (income) counties. This corresponds to a 2.61% (3.48%) increase compared to the weighted average. Our findings highlight that communities facing economic stress are more likely to engage in violent behaviour in response to warmer temperatures.

Finally, we explore whether the relationship IPV-temperature varies across racial and ethnic groups. In columns 4-6, we report the interaction terms between temperatures and counties with above median share of the a specific race. We find that temperature and IPV are significantly associated only in counties with predominantly white people, and below-median black and Hispanic population. However, the magnitudes are very similar among different categories, making difficult to draw conclusions on significant differences across races.

[12]High temperatures may discourage outdoor activities (Graff Zivin and Neidell, 2014) and exacerbate feelings of isolation (Mullins and White, 2019).

Extensive and intensive margin of violence. Warmer temperatures might either exacerbate the severity and frequency of existing IPV cases (intensive margin) or increase the likelihood of new IPV cases (extensive margin) or both. We examine whether one of the two margins prevails in Appendix Table A19. As a measure of intensive margin, we show that a 1°C increase in daily temperature is associated with 0.01 additional IPV cases per 100,000 people (15% at the mean), when excluding jurisdictions with zero cases on that date (column 1). We also find a positive, significant, but smaller in magnitude effect of temperature on IPV cases using a binary variable if at least one IPV case is recorded on that day as outcome (1°C increase is associated with a 0.03 percentage points increase in the probability, i.e., 1% at the mean). Shedding light on which of the two margins prevails is critical for policy implications. Given our results, increasing monitoring and enforcement of restraining orders in particularly hot days might be a more cost-effective solution than broad-based interventions.

Climatic conditions. There are numerous ways in which people and communities adapt to their current climate, including biological acclimatization, infrastructure investments, architectural styles, cooling appliances (e.g. air conditioning). Although it is beyond the scope of this paper to identify each heterogeneity component of adaptation, we finally examine the role of long-term climatic conditions as a proxy for behavioral and physiological adaptation. If any form of adaptation is taking place, we would expect that the effect of temperature diminishes as we move along the climate distribution, from colder to warmer counties. Our estimates (Appendix Table A20) suggest that average daily temperature increases the number of IPV cases on females especially in the warmer counties (defined as the top-tercile of the 30-year mean of average daily temperature). The effect is about two to five times larger than in cold and temperate counties, suggesting no evidence of a mediating effect of climate adaptation. This finding is in contrast with the literature on physical health (Heutel et al., 2021), but it is consistent with findings on the relationships between temperature and mental health, and between temperature and violence (Mullins and White, 2019; Evans et al., 2023).

4 Opioid reformulation in temperature-induced IPV

Armed with our findings of a positive effect of temperature on IPV that is stronger in counties with higher opioid prescriptions, we explore whether the OxyContin reformulation in 2010 has amplified or reduced the impact of temperature.

4.1 A triple difference approach

We design a triple difference (TD) specification which combines pre-reformulation county-level exposure to prescription opioids with within-county variation in temperature before and after the policy. We estimate the following specification:

$$Y_{idmy} = f(T_{c(i)dmy}, exposure_c, post_y) + g(P_{c(i)dmy}) + \mu_{imy} + \phi_{wy} + \delta_{dw} + \varepsilon_{idmy} \quad (2)$$

where we interact daily county-level temperature $T_{c(i)dmy}$ with county-level pre-2010 exposure to prescription opioids ($exposure_c$) and an indicator variable $post_y$ which takes value of one for the post-reformulation period, starting from 2010.

As in Equation 1, we control for precipitation and account for jurisdiction-month-year, week-of-year, day-of-week fixed effects. We also include year-specific temperature controls, accounting for time-varying changes in the direct effects of temperature. This implies that we focus on identifying the relative effect of temperature between high- and low-exposure mean opioid prescriptions per capita before and after the reformulation.

The coefficient on the triple interaction term is identified under the assumption that the temperature-IPV relationship would have stayed constant had the opioid reformulation not occurred. We account for month-year jurisdiction-specific unobserved heterogeneity, which provides further support for the assumption that within-jurisdiction variation in daily temperature is uncorrelated with other unobserved factors that may also affect the probability of intimate partner violence.

To rule out any potential differential pre-intervention trends between high- and low-exposure counties to prescription opioids, we also estimate two dynamic specifications. In the first one, we allow for temporal heterogeneous effects of the policy by time window after the intervention. We interact temperature 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-onwards). In a second specification, we estimate an event study design where daily temperature and pre-2010 exposure to prescription opioids are interacted with a set of event year coefficients for each of the 16 years in the sample. Thus, we identify differences in the temperature-IPV relationship between counties with high and low pre-intervention exposure in year y compared to 2010, the year OxyContin was reformulated. This specification also sheds light on potential dynamics behind the evolution of the treatment effect evolves over time.

We estimate Equation 2 using weighted-least squares where the weights are the average population in the jurisdiction during the sample period. Standard errors are clustered at the county-level.

4.2 Results

A preliminary visual inspection of the regression-adjusted relationship between temperature and intimate partner violence cases 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 (Appendix Figure A5). This result suggests that the opioid reformulation has a mitigating effect on the relationship between temperature and IPV in counties with greater exposure to opioids.

To provide further evidence on the role of the opioid reformulation, Figure 1 and Table A21 displays the results from the triple difference (TD) research design. The graph on the left-hand side reports the coefficient on the triple interaction term, which is negative and statistically significant. We find that a 1°C increase in temperature is associated with 0.0127 fewer IPV cases per 100,000 people after the reformulation occurred in 2010, a 16.8% reduction compared to the average IPV penetration rate before the reformulation policy (0.076). Compared to the estimated effect of the interaction between temperature and pre-reformulation opioid prescription (0.0134), the results suggest that the opioid reformulation strongly attenuates the temperature-IPV relationship, mitigating on average 94% of its effect.

On the right-hand side, we explore the potential temporal dynamics behind the attenuation role of the OxyContin reformulation in the temperature-IPV relationship. The coefficient on the triple interaction with the pre-policy time indicator is small in magnitude and not statistically significant at conventional levels, allaying concerns on differential pre-intervention trends. In the post-policy period, the short-, medium- and long-run coefficients are negative and statistically significant at the 95% level. The coefficients are marginally, but not significantly, smaller in magnitude over time suggesting a persistent effect of the policy over time.

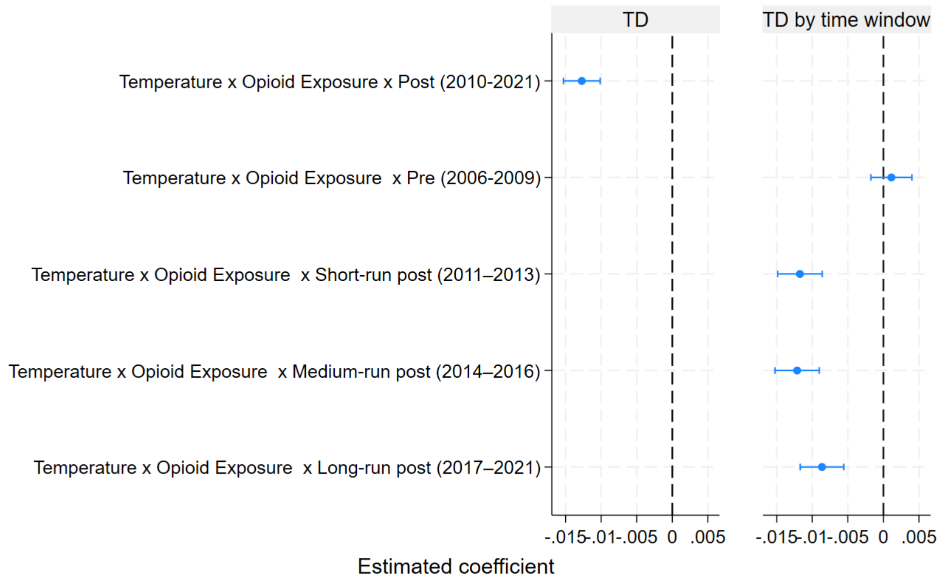
Our results are robust to a variety of alternative specifications that account for year-specific precipitation slopes (Appendix Figure A7); cluster standard errors at the state level (Appendix Figure A8); restrict the sample to different seasons (Appendix Figure A9) and different climates (Appendix Figure A10); use as exposure variable the number of opioid pills and shipments per capita from the ARCOS database (Appendix Table A23); aggregate the sample at the jurisdiction-year and jurisdiction-month levels (Appendix Table A22); and drops agencies that do not report for all the months of the year (Appendix Table A24).[13]

Figure 2 presents an event study visualization of our results. We report point estimates and 95% confidence intervals on the triple interaction terms between daily temperature, pre-reformulation opioid exposure, and year indicators, with 2010, the year in which OxyContin was reformulated, normalized to zero. As before, 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 intimate partner violence cases per 100,000 inhabitants decreases in high-exposure counties relative to low-exposure counties. The responsiveness of the temperature-IPV relationship decreases in high-exposure resulting in an average relative decrease of 0.01 IPV 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 Intimate Partner Violence (IPV) emerge only from 2012, two year after the implementation. Subsequently, the policy-induced attenuation of the temperature effect remains persistent and similar in magnitude over time. A plausible explanation for the delayed efficacy of the

[13]We also test for the effect of the OxyContin reformulation on IPV unconditional to temperature and document that the policy effectively reduces IPV cases (columns 1-3, Appendix Table A25) (Dave et al., 2023).

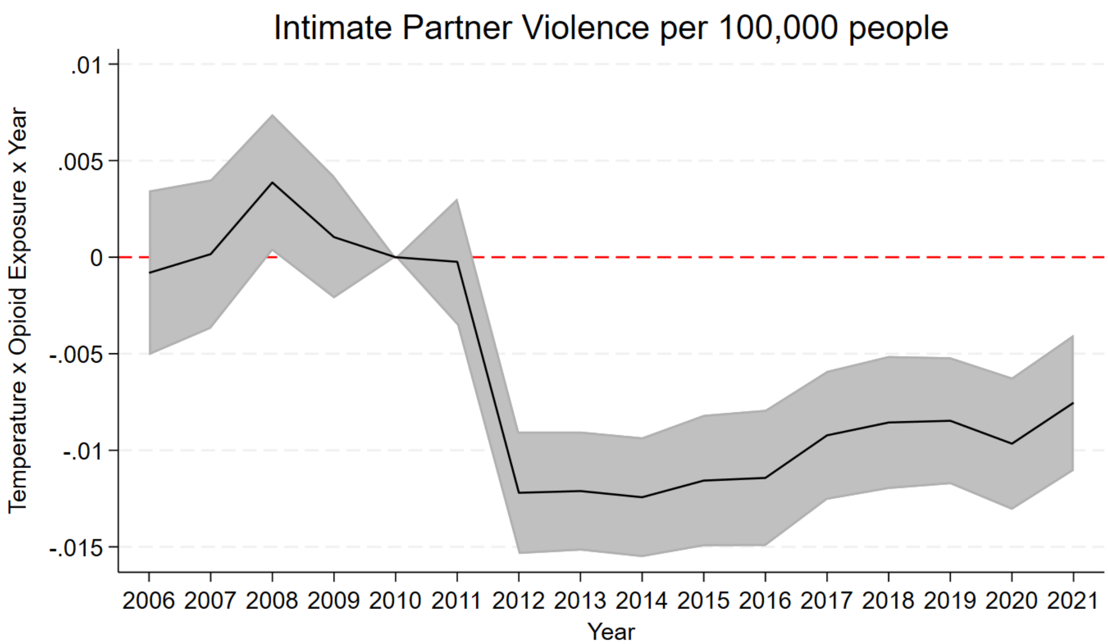
Figure 1: Triple difference (TD) of Opiod reformulation policy in 2010 on the temperature-IPV relationship



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 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.

policy in reducing climate sensitivity lies in the potential repercussions of abruptly curbing opioid intake. This cessation may precipitate withdrawal symptoms, spur substitution with substances offering intoxicating effects, and collectively exacerbate dependency while heightening emotional states among individuals in the initial post-policy period. To provide additional support to this hypothesis, we estimate an event-study allowing for month-year specific dynamic effects (Appendix Figure A6). Also in this case, reassuringly, results do not support the hypothesis of differential trends in temperature-IPV between higher and lower opioid exposure before the reformulation. Most importantly, the policy attenuates the effect of temperature on IPV starting from 2012 at the monthly level. The magnitude of the effect is relatively stable until the end of the time period considered, although becoming slightly noisier in the more recent years.

Figure 2: Event study of the differential effect of Opiod reformulation on the temperature-IPV relationship



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 IPV cases per 100,000 people. The regression also controls for year-specific temperature and precipitation coefficients, jurisdiction-month-year, week-of-year and day-of-week fixed effects. Shaded area represent the 95% confidence intervals with standard errors clustered at the county-level.

5 Mechanisms

In this section, we discuss and test for the potential channels through which opioid reformulation attenuates the temperature-IPV relationship.

5.1 Complementarity with other substances

Opioid addiction and misuse is usually associated with the use of complementary substances (Compton et al., 2021). This complementarity might contribute to violent behaviors towards partners during hot days. As a result, the reformulation of OxyContin may have reduced temperature-induced IPV offenses since, by affecting opioid users' behavior in abuse of other substances, notably alcohol, commonly linked with IPV (Schilbach, 2019).

Substance-involving cases. We test for potential complementarities with other substances by exploring the heterogeneous effects of the policy across IPV cases involving substances. We find that the policy was effective in reducing temperature-induced IPV cases when alcohol or marijuana were involved. In line with the baseline results, we do not find that the reformulation was effective for cocaine- and heroin-related offenses. This result suggests that for temperature-induced IPV the policy has not led to a substitution of oxycodone with heroin.[14]

Temperature and alcohol consumption. Alcohol consumption has been associated with prescription opioid overdoses and misuse (Esser et al., 2021), with binge drinkers twice more likely than non drinkers to misuse prescription opioids (Esser

[14]We also explore the effect of the policy on substance-involved IPV cases unconditional to temperature and document that the reformulation has increased the number of heroin-related IPV cases and reduced alcohol-related IPV offenses (Appendix Table A25) (Dave et al., 2023).

Table 3: Triple difference results on IPV cases involving substance use

	Female Intimate Partner Violence per 100,000 people					
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Alcohol	Cocaine	Heroin	Marijuana	Other Drugs
Temperature × Exposure	0.0135***	0.00323***	0.0000270	-0.00000374	0.000113**	0.0000506
	(0.00128)	(0.000375)	(0.0000204)	(0.00000318)	(0.0000564)	(0.0000421)
Temperature × Exposure × Post	-0.0127***	-0.00310***	-0.0000273	0.00000337	-0.000103*	-0.0000503
	(0.00130)	(0.000374)	(0.0000203)	(0.00000324)	(0.0000562)	(0.0000419)
Observations	31,326,025	31,326,025	28,843,459	28,843,459	28,843,459	28,843,459
Mean Outcome	0.07574	0.01308	0.00005	0.000005	0.0004	0.0001
Temperature-Year FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *Post* is a dummy variable equal to one for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to prescription opioids. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

et al., 2019). Table 3 suggests that the policy is particularly effective at reducing temperature-induced alcohol-related cases of intimate partner violence. We so hypothesise that the policy is effective for alcohol-related cases because it reduces the complementarity in the use of the two substances. We provide additional evidence in support of this mechanism using individual data from the BRFSS to explore whether hot days increase alcohol consumption, particularly in the form of heavy drinking, and if the association is exacerbated in most opioid-exposed counties.[15]

[15] We estimate the following regression:

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

where Y_{idmy} is a dummy equal to one if individual i drank heavily in the month before the interview; $T^{30d}_{c(i)dmy}$ and $P^{30d}_{c(i)dmy}$ are the 30-day mean of daily average and the 30-day sum of daily total precipitation prior to the interview date; and $H_{c(i)}$ is a binary indicator equal to one if a county is above 75$^{\text{th}}$ percentile of the pre-2010 opioid exposure. We also account for county ($\mu_{c(i)}$), calendar date (ϕ_{dmy}), and state-month fixed effects ($\delta_{s(i)m}$). We cluster standard errors at the county level, and we estimate the regression using the provided sample weights at the individual level. Obradovich

We find that a 1°C increase in daily average temperature is associated with an increase in the likelihood of heavy drinking in the previous month by 0.04-0.06 percentage points, a 0.58-0.77% increase compared to the mean (Table 4, columns 1-3). We also find a positive and significant relationship with an indicator for alcohol consumption and with the number of alcoholic drinks in the last month (Appendix Table A31), in line with contemporaneous analysis (Cohen and Gonzalez, 2024).

When we allow for heterogeneous effects by opioid exposure (column 4), we find that the effect is more pronounced in counties with high-level of exposure to opioid prescriptions. In these areas, a 1°C increase in daily average temperature in the previous month is associated with an increase in the likelihood of heavy drinking by 0.07 percentage points, a 0.98% at the mean. In less exposed counties, the effect is still positive, but halved and not significant. Interestingly, the interaction coefficient is less precisely estimated when the outcomes are any alcoholic drink or the number of alcoholic drinks (Appendix Table A33), suggesting that in high-opioid exposed communities temperature is mainly associated with compulsive alcohol consumption.

Altogether, our results suggest that alcohol consumption, particularly for heavy drinkers, is a key driver for temperature-induced intimate partner violence on female. Since opioid addicted people are also likely to be addicted to alcohol, our estimates suggest the reformulation of OxyContin may have then reduced the co-addiction to both substances.

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et al. (2018) employs a similar specification to study the impact of temperature on mental health using data from the Selected Metropolitan/Micropolitan Area Risk Trends of BRFSS SMART.

Table 4: Impact of temperature on alcohol consumption

	Heavy Drinking (Yes = 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
BRFSS Controls			✓	✓
County FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
State-Month FE		✓	✓	✓
Sample Weights	✓	✓	✓	✓

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. "BRFSS Controls" include education level, employment status, age, number of family member, and race. Standard errors are clustered at the county level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

5.2 Complementarity with other policies

We also explore the extent to which the effect of Oxycontin reformulation for temperature-driven IPV may be accentuated or mitigated by other policies that were taking place (Table 5).

Medical marijuana laws. First, we test whether the availability of medical marijuana mediates the effects of opioid reformulation on the temperature-IPV relationship through therapeutic substitution effects. We find that in states where medical marijuana is not accessible, the policy is effective at mitigating the harmful effect of temperature (columns 1-2). When medical marijuana is legally accessible, and thus more available as a therapeutic substitute, we do not document a significant effect of the policy in reducing the sensitivity of IPV to temperature. Although associative, these results suggest that access to medical marijuana dampens the substitution to more destructive and uncontrolled substances such as heroin, and mutes the co-benefits of the opioid reformulation on the effect of temperatures.

Substance-abuse treatment facilities. Second, we consider the extent to which the presence of substance-abuse treatment clinics influences the mitigation effect of the reformulation. We find that the policy is effective only in counties where SAT establishments are present (columns 3-4). We also document that the concentration of SAT establishments in its intensive margin, as measured by counties with SATs above the sample median, matters (columns 5-6). These results suggest that a supportive infrastructure against substance misuse/abuse in a community critically complements the attenuation effect of the reformulation on temperature and IPV.

Table 5: Triple difference results on IPV cases — Other Substance Abuse Regulation Policies

	Female Intimate Partner Violence per 100,000 people					
	Medical Marijuana Law		Substance-abuse Treatment Facilities			
	Without	With	Without	With	Below Median	Above Median
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × Exposure	0.0136***	0.00232	0.0015	0.0146***	0.0018	0.0167***
	(0.00137)	(0.00161)	(0.0016)	(0.0014)	(0.0014)	(0.0016)
Temperature × Exposure × Post	-0.0127***	-0.00216	0.0015	-0.0141***	-0.0002	-0.0160***
	(0.00142)	(0.00162)	(0.0019)	(0.0014)	(0.0016)	(0.0017)
Observations	24,699,212	6,626,813	3,094,215	15,567,979	4,414,440	11,153,539
Mean Outcome	0.063	0.736	0.7291	0.0310	0.0376	0.0304
Temperature-Year FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *Post* is a dummy variable equal to one for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to prescription opioids. In columns 3 to 6 the sample is restricted to the period 2006-2016. In columns 5 to 6 the sample is restricted only to counties with at least one substance-abuse treatment facility. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

5.3 Heterogeneous effects of the policy

We analyze how the attenuation effect of the opioid reformulation on the temperature-IPV gradient is heterogeneous across a variety of characteristics at the county-level. We estimate Equation 2 by splitting our estimation sample between counties above and below the sample median in terms of urbanization level, education levels, income and poverty measures.

Urban-rural divide. Greater population density may induce a differentially stronger attenuation effect of opioid reformulation in urban areas if IPV is more responsive to temperature in these areas. Conversely, urban areas may facilitate access to opioid substitutes such as illegal substances which can themselves induce increases in IPV and exacerbate the IPV elasticity to temperature. We empirically examine which of these two mechanisms prevails and show in Appendix Table A26 (columns 1-2, panel A) that, although main coefficients are close in magnitude in the two sub-samples, the effect at the mean is substantially larger in rural areas (39% vis-à-vis 0.6% in urban areas). Opioid reformulation mitigates the temperature-IPV gradient more effectively in rural areas, in line with previous temperature-homicide studies that document a similar heterogeneous effect for gun law restrictions effectiveness (Colmer and Doleac, 2023). A potential explanation that individuals in rural areas may have fewer alternative options for obtaining opioids or opioid substitutes, so the reformulation may have a more pronounced effect in reducing opioid misuse and, consequently, IPV in rural areas.

Education level. We also document that policy is effective in counties where the rate of individuals with at least high-school education is above the sample median (columns 3-4, panel A). Individuals with higher levels of education tend to have greater health literacy and awareness of the risks associated with opioid misuse and thus may be more receptive to public health campaigns as a result of the opioid reformulation. Therefore, when opioids are reformulated to deter abuse, these individuals are more likely to understand the rationale behind the policy and comply with it, leading to a more significant reduction in opioid misuse and temperature-induced IPV.

Economic stress. Finally, we show that policy is effective in richer counties where income per capita and labor force participation rate are above the median (columns 1-4, panel B). Greater access to alternative coping mechanisms in richer counties, such as mental health services, recreational activities, and community support could help reduce the reliance on opioids as a coping mechanism for stress and pain. In these counties, the policy might reinforce existing support systems.

5.4 Alternative mechanisms

Finally, we test for a set of alternative mechanisms that may explain the effectiveness of the policy in mitigating the temperature effects.

Access to Fentanyl from Mexico. At the time of the reformulation, there was a readily available substitute for OxyContin, fentanyl, with most of the production and trafficking coming from the Southwest Border through Mexican criminal groups (Evans et al., 2019). Mexican criminal organizations were often found to be responsible for distribution of fentanyl-laced counterfeit pills, a synthetic opioid fifty times stronger than heroin (Drug Enforcement Administration, 2020). We test whether the effectiveness of the policy depends on the distance between a county and the closest Mexican border crossing, as a measure of potential permeation of illegal substitute products such as fentanyl-laced pills.[16] We find that the effect of the policy is stronger in counties further away from the US-Mexican border, suggesting different effects by access to potential illicit substitutes trafficked from Mexico (Appendix Table A30).

Crime time of the day and sleep deprivation. Opioid abuse can damage sleep duration and quality (Bertz et al., 2019), and increases in nighttime temperatures can amplify nights of insufficient sleep and deteriorate sleep quality (Minor et al., 2022; Obradovich et al., 2017). These two effects combined might diminish the ability to cope with stress, leading individuals to respond to aversive stimuli in an aggressive manner (Rauer and El-Sheikh, 2012). We explore whether the reformulation of opioid prescription can help moderate the effect of temperature in specific

[16] We obtained the geographic coordinates of US/Mexico border crossings from the Bureau of Transportation Statistics (BTS, 2024), limiting the analysis to crossings that can be accessed by pedestrians, private vehicles, or buses. We then computed the travel distance from the population centroid of each county to the geographic coordinates of the nearest border crossing.

times of the day, for instance, by alleviating the sleep deprivation channel. We document a strong negative effect of the policy on the temperature-IPV relationship for crimes committed at all times of the day considered (morning, evening, afternoon, night) (Appendix Table A28). Therefore, we do not find conclusive evidence that the supply-side shock induced by the policy has differential effects.

Social interactions. Intimate partner violence is a crime that can occur at home or outside. Increases in temperature could affect criminal activity by increasing the likelihood of social interaction. Our baseline results confirm this intuition since we document a negative effect of rainier days on IPV. We test whether opioid reformulation has a differential effect on IPV crimes in different locations in two ways. First, we document that policy does not significantly affect the precipitation-IPV relationship at any conventional level (Appendix Figure A11). Second, we examine the effect of the opioid reformulation on the temperature-induced IPV cases by location of the crime. We find no significant difference between indoor and outdoor IPV cases, with the policy being effective at mitigating the climate sensitivity for both (Appendix Table A29). Altogether, these results suggest that opioid reformulation does not differentially affect IPV offenses that are more likely to arise in contexts with greater social interaction.

Type of offense. We also examine if the policy is effective at mitigating certain types of IPV offenses caused by temperature (Appendix Table A27). Our results indicate that the supply shock in opioid availability reduces IPV cases that involve assault (0.7%), while the effect is weakly significant for rapes, and it is not significant for murder cases. There is no statistically significant difference in the effect of the policy on cases that involve a firearm and those that do not, although the reduction is lower for those that do not involve firearms.

6 Discussion and conclusions

Our study examines how policies that do not deliberately aim at reducing sensitivity to environmental stressors can attenuate the effect of temperature on violent behavior. We address this question using administrative daily-level data in the Unites States over the past three decades and combine two quasi-experimental research designs to show how the 2010 OxyContin reformulation has unintendedly attenuated the relationship between temperature and intimate partner violence on females.

Using triple-difference and event-study designs, our findings reveal a positive association between higher temperatures and IPV rates. However, after the opioid reformulation, the relationship weakens, with a reduction of the effect of temperature by 94% in an average opioid-exposed county. The event-study analysis suggests that the policy's moderating effect is strongly persistent over time. The policy has been particularly effective in rural and richer counties, and where potential substitutes like marijuana are not legally available.

These findings reveal that the reformulation policy implemented in 2010 has had substantial benefits which may have not been accounted for in previous cost-benefit and impact evaluation analyses. This result is particularly important in a context where the policy has also been shown to have potential un-intended negative consequences, such as an increase in child maltreatment (Evans et al., 2022).

Armed with the estimates of our baseline specification, we conduct a back-of-the-envelope calculation to monetize the net social benefit of the opioid reformulation policy on the temperature-IPV relationship and compare it to other policies implemented. We estimate that, on average, after OxyContin reformulation one-degree Celsius increase is associated with 4,910 fewer cases of IPV on females in counties with high exposure to opioid prescriptions at the baseline (75th percentile) relative to low-exposure counties (25th percentile). For the same interquartile shift in opioid exposure, using the lifetime cost of an intimate partner violence of $135,556 (in $2023) from Peterson et al. (2018), we calculate that, on average, the policy has generated in the after-reformulation period an annual social benefit of approximately $665.547 million (in $2023) for one-degree Celsius increase in average daily temperature.[17]

This expected social benefit is economically meaningful. To illustrate, it is equivalent to the establishment of 74 additional Substance Abuse Treatment Facilities facilities (Bondurant et al., 2018),[18] and 1263 new mental healthcare facilities (Deza et al., 2022).[19] Moreover, it has also reduced the economic burden associated with funding key federal policies introduced in the United States to contrast opioid abuse and domestic violence. Notably, our estimated social benefit is approximately equivalent to almost 4 years of funding for the Comprehensive Addiction and Recovery Act (CARA),[20] 20% of the budget for the Violence Against Women Act (VAWA),[21] and 12.5 supplemental funding allocations to the Family Violence Prevention and Services Act (FVPSA).[22] This back-to-the-envelope estimate high-

[17] This is obtained as follows: -0.0127 IPV cases per 100,000 people $\times$ 365 (days) $\times$ Average population between 2006-2009 $\times$ 0.35 (opioid prescription interquartile range) $\times$ $135,556 (lifetime cost of an IPV case) $\times$ 1 (degree Celsius change in temperature).

[18] 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).

[19] 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.

[20] 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.

[21] 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.

[22] 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

lights the substantial beneficial welfare-enhancing role of the opioid reformulation policy in mitigating the effect of temperature on IPV.

Our research opens avenues for crucial future investigations at the intersection of policy dynamics and environmental influences on social outcomes. Our findings provide new evidence about how the policy context may change the relationship between temperature exposure and social outcomes. Notably, we broaden the scope of understanding the effects of policies that do not directly target climate adaptation but can either mitigate or exacerbate climate impacts. Our study highlights unexpected positive externalities from the Oxycontin reformulation policy, designed to address opioid abuse. Understanding the broader, unintended consequences of policies, and revealing their capacity to shape how environmental factors influence welfare-related outcomes is a crucial agenda for future research.

Services Act Program.

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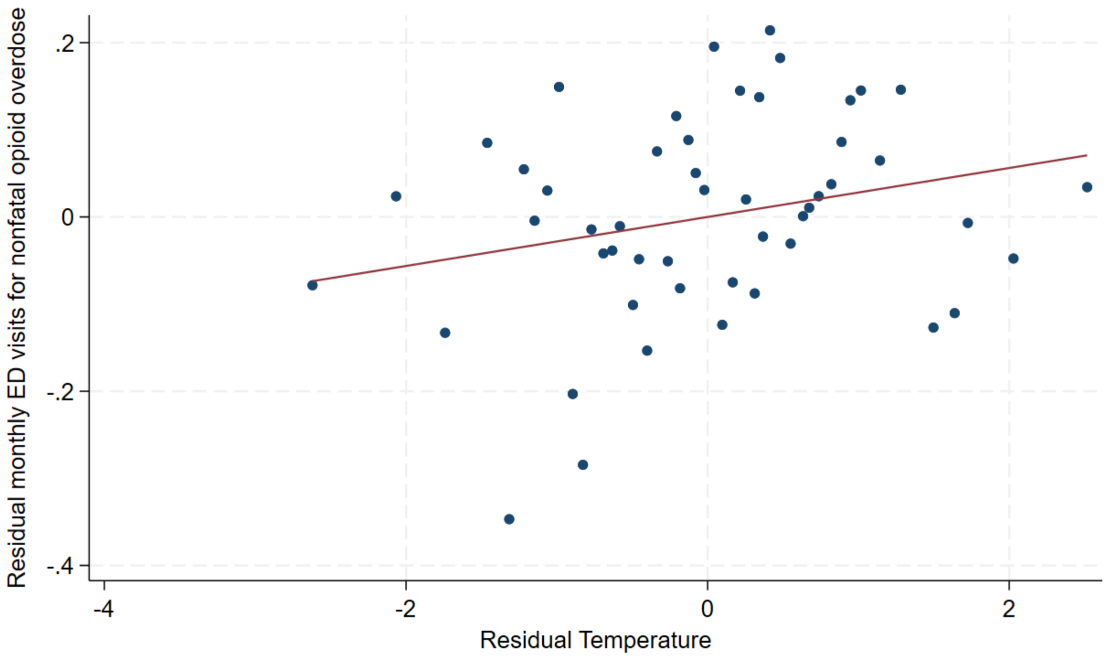
A Online Appendix

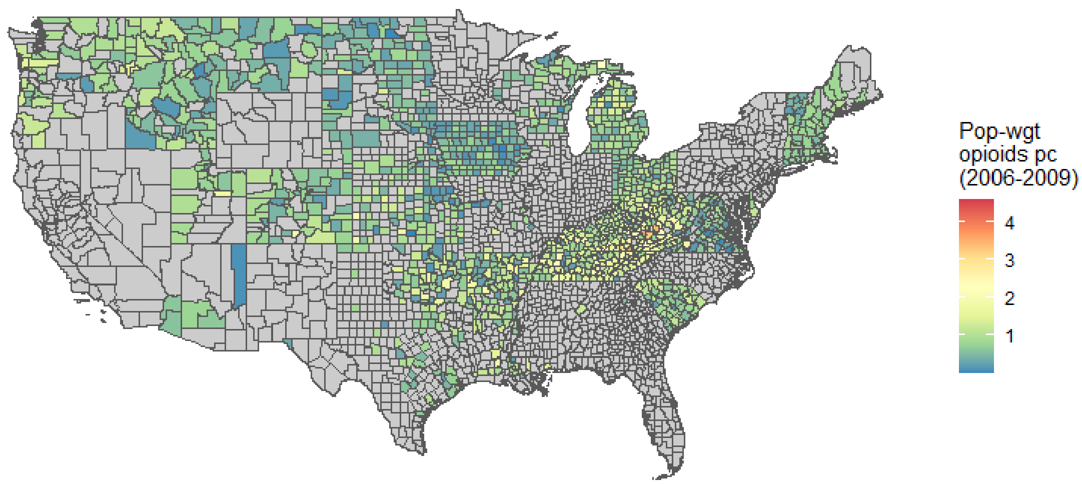
A.1 Additional Figures

Figure A1: Temperature and non-fatal opioid-related emergency department visits



Notes: Figure shows binned scatterplots with 50 bins and a linear regression on the underlying data on the correlation net of state-month, state-year, month-year fixed effects between residualized monthly rate of ED visits for nonfatal opioid overdose and residualized temperature at the state level for the 2018-2021 period. Coefficient: 0.0281 (SE = 0.014). Data on Nonfatal Opioid-related Overdose Emergency Department visits come from Centers for Disease Control and Prevention (2024).

Figure A2: 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 1,345 counties in the final estimation sample. Sample mean is 0.84, standard deviation is 0.23.

A.2 Additional Results

A.2.1 Temperature and Intimate Partner Violence: Robustness

Table A1: The Relationship between Temperature and Intimate Partner Violence — Accounting for Covid-19 period

	Female Intimate Partner Violence per 100,000 people	
	1991-2019	1991-2021
	(1)	(2)
Temperature (°C)	0.0004**	0.0005**
	(0.0002)	(0.0002)
Precipitation (m)	-0.0138	-0.0126
	(0.0091)	(0.0102)
Observations	37,687,828	44,170,732
Mean Outcome	0.04676	0.05742
Week-of-Year FE	✓	✓
Day-of-Week FE	✓	✓
Jurisdiction-Month-Year FE	✓	✓
Covid Dummy		✓
Jurisdiction-Location Population Weights	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. In Column 2 we include a dummy (0,1) from 2020 onwards to identify the years of Covid-19 outbreak. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A2: The Relationship between Temperature and Intimate Partner Violence — Trimming the Sample

	Female Intimate Partner Violence per 100,000 people		
	IPV < 100	IPV < 10	IPV < 1
	(1)	(2)	(3)
Temperature (°C)	0.0005**	0.0004**	1.81e-05*
	(0.0002)	(0.0002)	(9.29e-06)
Precipitation (m)	-0.0126	-0.0097	-0.0004
	(0.0101)	(0.0089)	(0.0009)
Observations	44,156,376	43,458,777	40,599,988
Mean Outcome	0.05258	0.04563	0.00452
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A3: Relationship between Temperature and Intimate Partner Violence — Count Dependent Variable

	# Female Intimate Partner Violence		
	OLS	PPML	PPML
	(1)	(2)	(3)
Temperature (°C)	0.0011***	0.0104***	0.0104***
	(0.0004)	(0.0016)	(0.0016)
Precipitation (m)	-0.0281	-0.1148	-0.1037
	(0.0560)	(0.3539)	(0.3541)
Observations	44,170,732	40,613,425	23,638,551
Mean Outcome	0.11771	0.11771	0.11771
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
State-Month-Year FE		✓	
Jurisdiction-Month-Year FE	✓		✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence cases on females. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A4: Relationship between Temperature and Intimate Partner Violence — Alternative Fixed-effects

	Female Intimate Partner Violence per 100,000 people			
	(1)	(2)	(3)	(4)
Temperature (°C)	0.0005**	0.0003*	0.0008***	0.0007***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Precipitation (m)	-0.0126	-0.0425	-0.0334*	-0.0189
	(0.0102)	(0.0264)	(0.0174)	(0.0152)
Cumulative Effect of Temperature				0.0003***
				(0.0001)
Cumulative Effect of All Temperature Leads				0.000258**
				(0.000106)
Cumulative Effect of 2nd to 7th Temperature Leads				-1.71e-05
				(5.00e-05)
Observations	44,170,732	44,170,732	44,170,732	43,979,205
Mean Outcome	0.05741	0.05741	0.05741	0.05741
Week-of-Year FE	✓	✓		
Day-of-Week FE	✓	✓		
Jurisdiction-Month-Year FE	✓		✓	✓
Jurisdiction-Day FE		✓	✓	✓
Date FE			✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

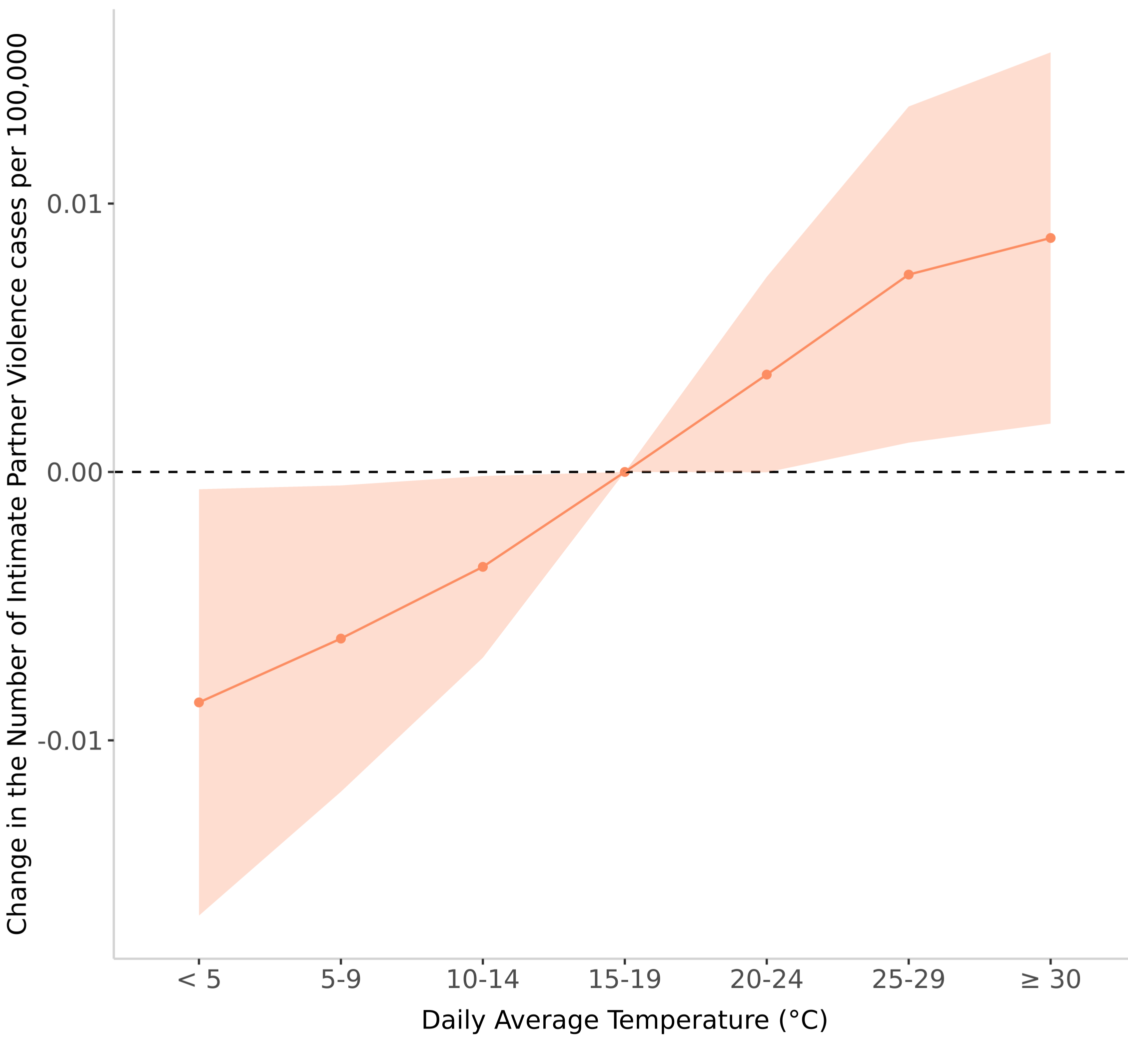
Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Column 1 reports the baseline results. In Columns 3 and 4 we use the same fixed effect specification from **?**. In Column 4 we also control for 7-day lags and leads. In the same column we report: (i) the cumulative effect of temperature, summing the coefficients of contemporaneous temperature and the 7-day lags; (ii) the cumulative effects of the temperature leads. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A5: Relationship between Temperature and Intimate Partner Violence — Alternative Standard Errors

	Female Intimate Partner Violence per 100,000 people	
	(1)	(2)
Temperature (°C)	0.0005**	0.0005*
	(0.0002)	(0.0002)
Precipitation (m)	-0.0126	-0.0126
	(0.0102)	(0.0116)
Observations	44,170,732	44,170,732
Mean Outcome	0.05741	0.05741
Week-of-Year FE	✓	✓
Day-of-Week FE	✓	✓
Jurisdiction-Month-Year FE	✓	✓
Jurisdiction-Location Population Weights	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. In Column (1) standard errors are clustered at the county level. In Column (2) standard errors are clustered at the state level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01

Figure A3: The Relationship between Temperature and Intimate Partner Violence — Temperature Bins



Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is modelled using seven 5-degree Celsius intervals. The coefficients indicate the effect of an additional day in the j-th bin on IPV cases per 100,000 people, relative to the reference interval 15-19 °C. The regression also controls for total daily precipitation measured in metres (m), jurisdiction-month-year, week-of-year and day-of-week fixed effects. The shaded area represents 95% confidence intervals with standard errors clustered at the county-level.

Table A6: The Relationship between Temperature and Intimate Partner Violence — Temperature Bins

	Female Intimate Partner Violence per 100,000 people				
	(1)	(2)	(3)	(4)	(5)
< 5 (°C)	-0.0189**	-0.0958***	-0.0086**	-0.0046	-0.0086**
	(0.0074)	(0.0298)	(0.0040)	(0.0032)	(0.0041)
5-10 (°C)	-0.0027	-0.0582***	-0.0062**	-0.0051**	-0.0062**
	(0.0021)	(0.0169)	(0.0029)	(0.0025)	(0.0029)
10-15 (°C)	-0.0027	-0.0312***	-0.0036**	-0.0037**	-0.0035**
	(0.0021)	(0.0087)	(0.0017)	(0.0016)	(0.0017)
20-25 (°C)	0.0095**	0.0379***	0.0037*	0.0044***	0.0036*
	(0.0041)	(0.0143)	(0.0019)	(0.0017)	(0.0019)
25-30 (°C)	0.0556***	0.0988***	0.0074**	0.0099***	0.0073**
	(0.0190)	(0.0311)	(0.0032)	(0.0029)	(0.0032)
≥ 30 (°C)	0.0933*	0.1379***	0.0089**	0.0133**	0.0087**
	(0.0525)	(0.0411)	(0.0036)	(0.0055)	(0.0035)
Precipitation (m)	0.1015	0.0954	-0.0017	-0.0153	-0.0002
	(0.1621)	(0.1022)	(0.0098)	(0.0180)	(0.0103)
Observations	44,170,732	44,170,732	44,170,732	44,170,732	44,170,732
Mean Outcome	0.05741	0.05741	0.05741	0.05741	0.05741
Month-Year FE		✓			
Week-of-Year FE		✓	✓	✓	✓
Day-of-Week FE		✓	✓	✓	✓
State-Month-Year FE			✓		
Jurisdiction FE				✓	
Jurisdiction-Month-Year FE					✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is modelled using temperature bins, where each bin is a dummy variable equal to 1 if the average temperature on a day falls within the specific bin. The omitted temperature category is 15-20 °C. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A7: The Relationship between Temperature and Intimate Partner Violence — Share of Hours

	Female Intimate Partner Violence per 100,000 people				
	(1)	(2)	(3)	(4)	(5)
< 5 (°C)	-0.0053	-0.0948***	-0.0194**	-0.0038	-0.0091**
	(0.0065)	(0.0271)	(0.0086)	(0.0035)	(0.0040)
5-10 (°C)	0.0191**	-0.0413***	-0.0117**	-0.0050*	-0.0062**
	(0.0076)	(0.0123)	(0.0048)	(0.0027)	(0.0027)
10-15 (°C)	0.0139**	-0.0138*	-0.0061***	-0.0031*	-0.0035***
	(0.0068)	(0.0080)	(0.0021)	(0.0016)	(0.0013)
20-25 (°C)	0.0294**	0.0713**	0.0117	0.0072**	0.0060
	(0.0127)	(0.0299)	(0.0073)	(0.0031)	(0.0038)
25-30 (°C)	0.0668**	0.1374***	0.0226*	0.0131***	0.0106*
	(0.0263)	(0.0472)	(0.0116)	(0.0041)	(0.0054)
≥ 30 (°C)	0.1128**	0.1750***	0.0315**	0.0186***	0.0157**
	(0.0512)	(0.0576)	(0.0137)	(0.0062)	(0.0067)
Precipitation (m)	0.1345	0.1596	0.0613	-0.0055	0.0091
	(0.1532)	(0.1081)	(0.0427)	(0.0172)	(0.0134)
Observations	44,170,732	44,170,732	44,170,732	44,170,732	44,170,732
Mean Outcome	0.05741	0.05741	0.05741	0.05741	0.05741
Month-Year FE		✓			
Week-of-Year FE		✓	✓	✓	✓
Day-of-Week FE		✓	✓	✓	✓
State-Month-Year FE			✓		
Jurisdiction FE				✓	
Jurisdiction-Month-Year FE					✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is modelled using temperature bins, where each bin is a share of hours during a day where hourly temperature falls within the specific bin. The omitted temperature category is 15-20 °C. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A8: Relationship between Temperature and Intimate Partner Violence — Polynomials (up to the 4th degree)

	Female Intimate Partner Violence per 100,000 people			
	(1)	(2)	(3)	(4)
Temperature (°C)	0.0005**	0.0003*	0.0003*	0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Temperature^2		1.51e-05**	1.45e-05**	1.71e-05**
		(6.02e-06)	(6.59e-06)	(8.62e-06)
Temperature^3			3.08e-08	2.43e-07
			(9.68e-08)	(1.51e-07)
Temperature^4				-8.88e-09
				(7.56e-09)
Precipitation (m)	-0.0126	0.0057	0.0060	0.0063
	(0.0102)	(0.0129)	(0.0126)	(0.0127)
Observations	44,170,732	44,170,732	44,170,732	44,170,732
Mean Outcome	0.05741	0.05741	0.05741	0.05741
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01

Table A9: The Relationship between Temperature and Intimate Partner Violence — Lags and Leads

	Female Intimate Partner Violence per 100,000 people				
	7-day Lags	14-day Lags	21-day Lags	7-day Leads	7-day Lags and Leads
	(1)	(2)	(3)	(4)	(5)
Contemporaneous Temperature (°C)	0.0005**	0.0005**	0.0005*	0.0004**	0.0004*
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Precipitation (m)	-0.0090	-0.0080	-0.0069	-0.0034	-0.0036
	(0.0101)	(0.0099)	(0.0104)	(0.0120)	(0.0108)
Cumulative Effect of Temperature	0.0003**	0.0002**	0.0002*		0.0002*
	(0.0001)	(9.42e-05)	(0.0001)		(8.82e-05)
Cumulative Effect of All Temperature Leads				0.0002*	0.0002*
				(0.0001)	(9.24e-05)
Cumulative Effect of 2nd to 7th Temperature Leads				4.25e-05	-1.25e-05
				(4.81e-05)	(2.32e-05)
Observations	44,074,951	43,979,170	43,883,389	44,074,986	43,979,205
Mean Outcome	0.05741	0.05741	0.05741	0.05741	0.05741
Week-of-Year FE	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. The cumulative effect of temperature is the sum of the coefficients of contemporaneous temperature and its lags. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A10: The Relationship between Nighttime Temperature and Intimate Partner Violence

	Female Intimate Partner Violence per 100,000 people		
	(1)	(2)	(3)
Nighttime Temperature (°C)	0.000521**	0.000505**	0.000495**
	(0.000250)	(0.000242)	(0.000238)
Precipitation (m)	0.000142	-0.00580	-0.00992
	(0.0128)	(0.0117)	(0.0109)
Observations	44,170,732	44,170,732	44,170,732
Mean Outcome	0.0574	0.0574	0.0574
Nighttime	6pm-6am	8pm-6am	8pm-8am
Nighttime Temperature Mean (°C)	12.31	11.82	11.28
Jurisdiction-Month-Year FE	✓	✓	✓
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

A.2.2 Temperature and Intimate Partner Violence: Heterogeneity

Table A11: The Relationship between Temperature and Intimate Partner Violence — Offenses

	Female Intimate Partner Violence per 100,000 people		
	Assault (1)	Rape (2)	Murder (3)
Temperature (°C)	0.0005**	4.53e-06*	-5.91e-08
	(0.0002)	(2.64e-06)	(2.31e-07)
Precipitation (m)	-0.0121	-0.0003	-0.0002
	(0.0102)	(0.0004)	(0.0002)
Observations	44,170,732	44,170,732	44,170,732
Mean Outcome	0.05647	0.00087	7.23e-05
Jurisdiction-Month-Year FE	✓	✓	✓
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓

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

Table A12: The Relationship between Temperature and Intimate Partner Violence — Non-Firearms vs Firearms

	Female Intimate Partner Violence per 100,000 people	
	No Firearms	Firearms
	(1)	(2)
Temperature (°C)	0.0004**	8.44e-06*
	(0.0002)	(4.32e-06)
Precipitation (m)	-0.0089	-0.0010
	(0.0095)	(0.0007)
Observations	43,779,771	43,779,771
Mean Outcome	0.04923	0.01102
Jurisdiction-Month-Year FE	✓	✓
Week-of-Year FE	✓	✓
Day-of-Week FE	✓	✓
Jurisdiction-Location Population Weights	✓	✓

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

Table A13: The Relationship between Temperature and Intimate Partner Violence — Location of the Crime

	Female Intimate Partner Violence per 100,000 people	
	Other	Residence
	(1)	(2)
Temperature (°C)	0.0001**	0.0004**
	(6.16e-05)	(0.0002)
Precipitation (m)	-0.0091**	-0.0034
	(0.0045)	(0.0096)
Observations	44,170,732	44,170,732
Mean Outcome	0.01083	0.04658
Jurisdiction-Month-Year FE	✓	✓
Week-of-Year FE	✓	✓
Day-of-Week FE	✓	✓
Jurisdiction-Location Population Weights	✓	✓

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

Table A14: The Relationship between Temperature and Intimate Partner Violence — Time of the Day

	Female Intimate Partner Violence per 100,000 people			
	Morning (1)	Afternoon (2)	Evening (3)	Night (4)
Temperature (°C)	6.57e-05**	9.30e-05**	0.0002**	0.0001**
	(3.20e-05)	(4.57e-05)	(9.13-05)	(7.19e-05)
Precipitation (m)	-0.0020	4.68×10^{-5}	-0.0009	-0.0099**
	(0.0016)	(0.0029)	(0.0037)	(0.0045)
Observations	44,110,994	44,110,994	44,110,994	44,110,994
Mean Outcome	0.00907	0.01353	0.02075	0.01332
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

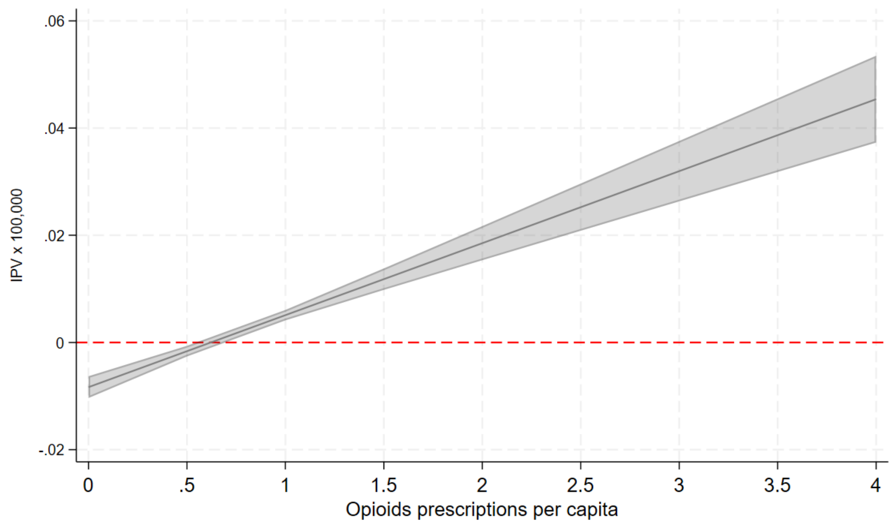
Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Standard errors are clustered at the county level.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

Table A15: The Relationship between Temperature and Intimate Partner Violence — Substance Use

	Female Intimate Partner Violence per 100,000 people					
	Alcohol	Heroin	Cocaine	Marijuana	Other Drugs	All Drugs
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (°C)	9.47e-05**	7.86e-08	-3.47e-08	2.40e-06*	1.77e-06*	4.22e-06*
	(4.82e-05)	(1.10e-07)	(1.47e-07)	(1.28e-06)	(9.32e-07)	(2.18e-06)
Precipitation (m)	-0.0010	-4.32e-06	0.0001	4.26e-05	-0.0003	-7.7e-05
	(0.0038)	(6.44e-05)	(0.0001)	(0.0003)	(0.0002)	(0.0003)
Observations	44,170,732	40,656,448	40,656,448	40,656,448	40,656,448	40,656,448
Mean Outcome	0.00985	1.94e-05	2.78e-05	0.00019	0.00284	0.00053
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓

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

Figure A4: Effect of temperature by opioid prescription exposure



Notes: The figure plots the marginal effect of temperature on IPV on female victims per 100,000 by population-weighted mean per capita opioid prescriptions for the pre-period policy 2006 to 2009.

Table A16: The Relationship between Temperature and Intimate Partner Violence — Opioid Exposure Before Reformulation (CDC)

	Female Intimate Partner Violence per 100,000 people		
	(1)	(2)	(3)
Temperature (°C)	0.0017	-0.0083***	
	(0.0013)	(0.0010)	
Precipitation (m)	-0.3694	0.1123	
	(0.8068)	(0.2456)	
Temperature × 2006-2009 Avg. Opioid Prescriptions	0.0046***	0.0134***	
	(0.0014)	(0.0013)	
Precipitation (m) × 2006-2009 Avg. Opioid Prescriptions	0.4913	-0.2495	
	(0.8918)	(0.3640)	
Temperature × Below Median			0.0002
			(0.0002)
Temperature × Above Median			0.0105***
			(0.0008)
Precipitation × Below Median			-0.0504
			(0.0465)
Precipitation × Above Median			-0.1567
			(0.2760)
Observations	6,021,556	6,021,556	6,021,556
Mean Outcome	0.0760	0.0760	0.0760
Jurisdiction-Month-Year FE	✓	✓	
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Month-Year × Median Exposure FE			✓
Jurisdiction-Location Population Weights		✓	✓

Notes: The sample is restricted to the period 2006-2009. The dependent variable is the number of intimate partner violence on females 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). In Columns 1 and 2 temperature and precipitation are interacted with the county-specific 2006-2009 average opioid prescriptions from the Centers for Disease Control and Prevention (CDC). In Column 3 temperature and precipitation are interacted with a dummy indicated whether a county is above the median level of the the county-specific 2006-2009 average opioid prescriptions from the Centers for Disease Control and Prevention (CDC). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A17: The Relationship between Temperature and Intimate Partner Violence — Opioid Exposure Before Reformulation (ARCOS)

	Female Intimate Partner Violence per 100,000 people			
	(1)	(2)	(3)	(4)
Temperature (°C)	0.0024**	-0.0046***		-0.0080***
	(0.0012)	(0.0012)		(0.0010)
Precipitation (m)	0.5416	0.0450		0.0339
	(0.7535)	(0.2544)		(0.2355)
Temperature × 2006-2009 Avg. Opioid Pills	9.81e-05***	0.0002***		
	(3.04e-05)	(3.18e-05)		
Precipitation × 2006-2009 Avg. Opioid Pills	-0.0137	-0.0033		
	(0.0186)	(0.0082)		
Temperature × Below Median			0.0003	
			(0.0003)	
Temperature × Above Median			0.0091***	
			(0.0005)	
Precipitation × Below Median			-0.0526	
			(0.0487)	
Precipitation × Above Median			-0.0824	
			(0.2256)	
Temperature × 2006-2009 Avg. Opioid Shipments				0.1312***
				(0.0119)
Precipitation × 2006-2009 Avg. Opioid Shipments				-1.323
				(3.765)
Observations	6,195,061	6,195,061	6,195,061	6,195,061
Mean Outcome	0.0760	0.0760	0.0760	0.0760
Jurisdiction-Month-Year FE	✓	✓		✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Jurisdiction-Month-Year × Median Exposure FE			✓	
Jurisdiction-Location Population Weights		✓	✓	✓

Notes: The sample is restricted to the period 2006-2009. The dependent variable is the number of intimate partner violence on females 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). In Columns 1 and 2 temperature and precipitation are interacted with the county-specific 2006-2009 average opioid pills from the ARCOS database. In Column 3 temperature and precipitation are interacted with a dummy indicated whether a county is above the median level of the county-specific 2006-2009 average opioid prescriptions from the ARCOS database. In Column 4 temperature and precipitation are interacted with the county-specific 2006-2009 average opioid shipments from the ARCOS database. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A18: The Relationship between Temperature and Intimate Partner Violence — County-level Socio-demographics

	Female Intimate Partner Violence per 100,000 people					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × Rural	0.0003					
	(0.0002)					
Temperature × Urban	0.0010***					
	(0.0003)					
Temperature × Poverty Rate (Below Median)		0.0003*				
		(0.0002)				
Temperature × Poverty Rate (Above Median)		0.0015**				
		(0.0006)				
Temperature × Income (Above Median)			0.0004*			
			(0.0002)			
Temperature × Income (Below Median)			0.0020**			
			(0.0008)			
Temperature × White % (Below Median)				0.0005		
				(0.0003)		
Temperature × White % (Above Median)				0.0004**		
				(0.0002)		
Temperature × Black % (Below Median)					0.0004**	
					(0.0001)	
Temperature × Black % (Above Median)					0.0005	
					(0.0003)	
Temperature × Hispanic % (Below Median)						0.0008***
						(0.0003)
Temperature × Hispanic % (Above Median)						0.0004*
						(0.0003)
Observations	44,160,870	44,168,174	44,168,174	44,160,870	44,160,870	44,160,870
Mean Outcome	0.05742	0.05742	0.05742	0.05742	0.05742	0.05742
Precipitation Controls	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Month-Year × Median Urban FE	✓					
Jurisdiction-Month-Year × Median Poverty Rate FE		✓				
Jurisdiction-Month-Year × Median Income FE			✓			
Jurisdiction-Month-Year × Median White (%) FE				✓		
Jurisdiction-Month-Year × Median Black (%) FE					✓	
Jurisdiction-Month-Year × Median Hispanic (%) FE						✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females 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). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A19: The Relationship between Temperature and Intimate Partner Violence - Intensive and Extensive Margins

	Female Intimate Partner Violence per 100,000 people	
	IPV > 0	Any IPV
	(1)	(2)
Temperature (°C)	0.0103***	0.0003***
	(0.0008)	(8.33e-05)
Precipitation (m)	-0.1892	0.0030
	(0.1341)	(0.0457)
Observations	3,924,606	44,170,732
Mean Outcome	0.06757	0.02906
Jurisdiction-Month-Year FE	✓	✓
Week-of-Year FE	✓	✓
Day-of-Week FE	✓	✓
Jurisdiction-Location Population Weights	✓	✓

Notes: In column 1 the dependent variable is the number of intimate partner violence on females per 100,000 people, but we exclude jurisdiction-day without cases. In column 2 the dependent variable is a dummy variable indicating if at least 1 IPV on female cases has occured. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01

Table A20: The Relationship between Temperature and Intimate Partner Violence — Climatic Conditions

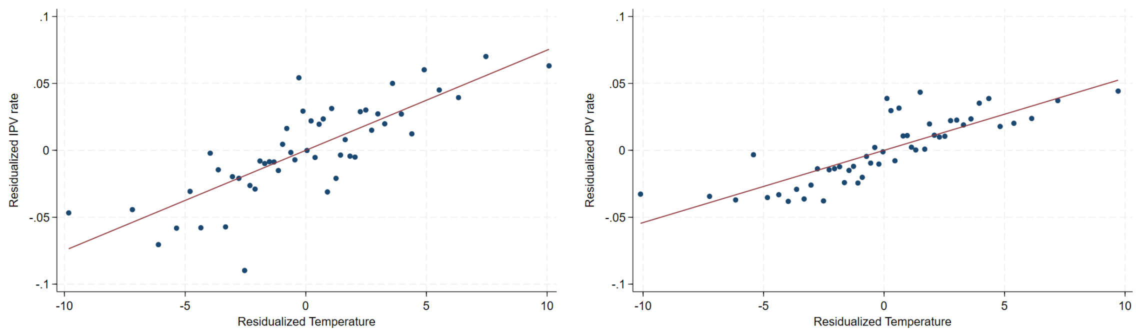
	Female Intimate Partner Violence per 100,000 people	
	(1)	(2)
Temperature × Cold	0.0043***	0.0003
	(0.0003)	(0.0002)
Temperature × Mild	0.0058***	0.0006**
	(0.0004)	(0.0002)
Temperature × Warm	0.0102***	0.0016**
	(0.0007)	(0.0007)
Observations	44,170,732	44,170,732
Mean Outcome	0.05742	0.05742
Precipitation Controls	✓	✓
Week-of-Year FE	✓	✓
Day-of-Week FE	✓	✓
Jurisdiction-Month-Year × Climate Terciles FE	✓	✓
Jurisdiction-Location Population Weights		✓

Notes: The dependent variable is the number of intimate partner violence on females 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). Counties are grouped based on terciles of their 30-year mean of daily average temperature. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

A.2.3 Opioid Reformulation

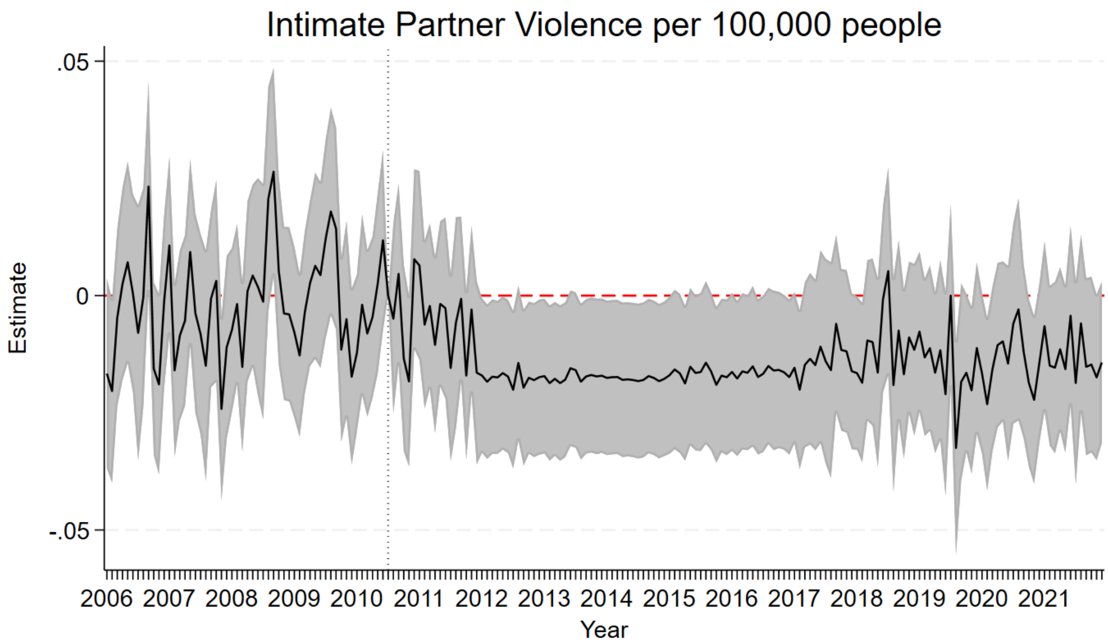
Figure A5: Temperature and Opioid prescription reformulation

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



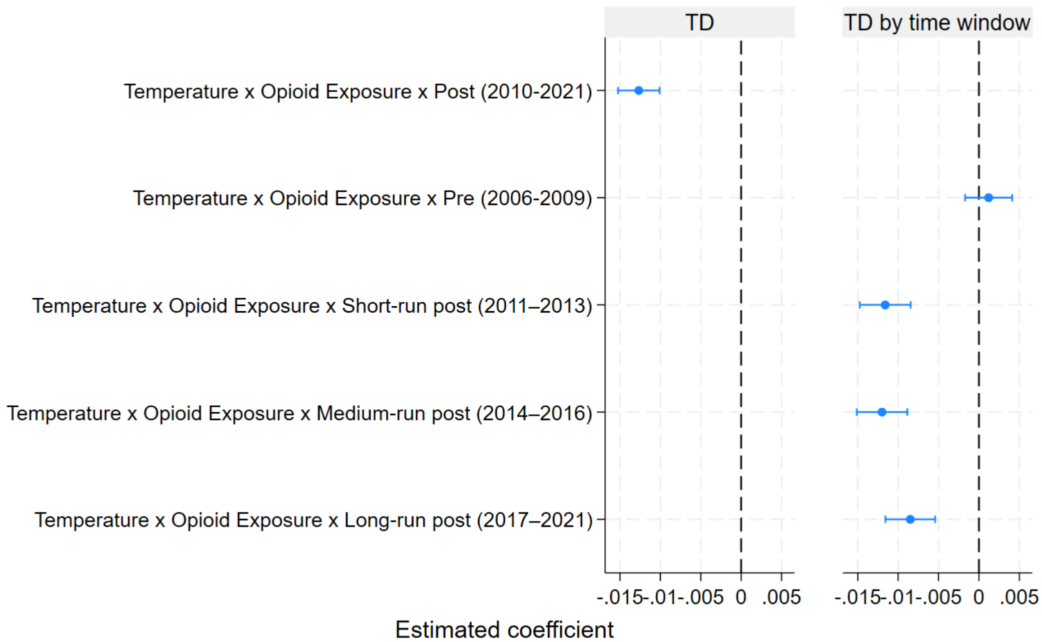
Notes: Panels (a) and (b) show binned scatterplots with 50 bins and a linear regression on the underlying data. Each shows the correlation net of jurisdiction-month-year, week-of-year, day-of-week fixed effects between residualized IPV rate and residualized temperature. The panels show the relationship for counties with above-median exposure to prescription opioids in the sample: (a) before the policy (2006-2009), and (b) after the Oxycontin reformulation (2010-2021).

Figure A6: Triple difference (TD) of Opiod reformulation policy on the temperature-IPV relationship at month-year 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 month-year dummies in a regression where the outcome variable is the number of IPV cases per 100,000 people. The regression also controls for month-year-specific temperature and precipitation coefficients, jurisdiction-month-year, week-of-year and day-of-week fixed effects. The dashed vertical line is on July 2010, one month before the policy is enacted. Shaded area represent the 95% confidence intervals with standard errors clustered at the county-level.

Figure A7: Triple difference (TD) of Opiod reformulation policy in 2010 on the temperature-IPV relationship (accounting for year-specific precipitation effects)



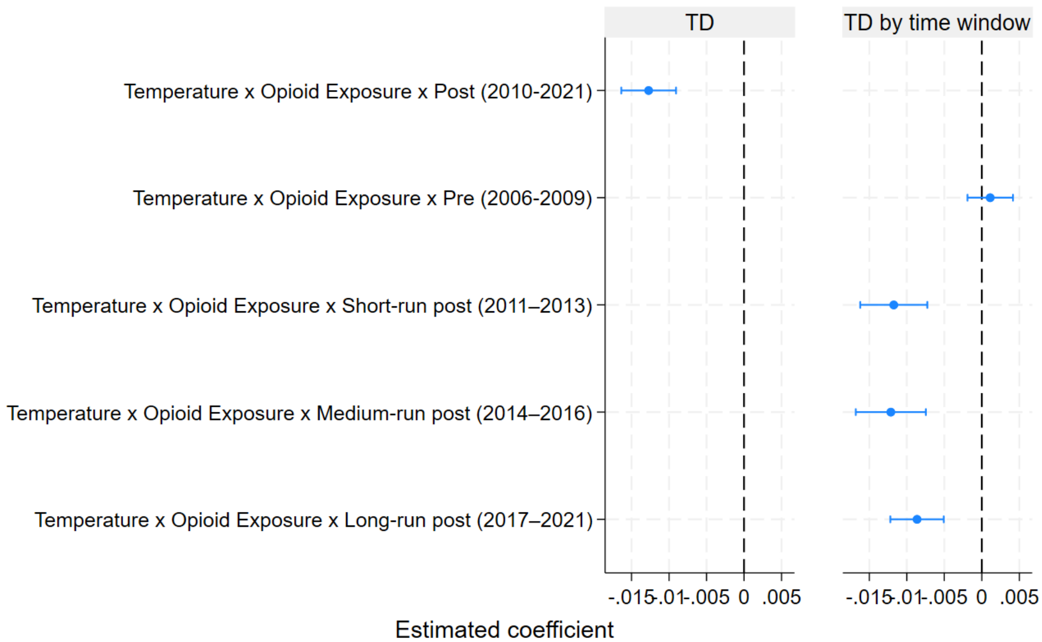
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opiod prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation 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, several years post-reformulation. The regression also controls for year-specific temperature and year-specific precipitation, 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.

Table A21: Triple difference: temperature, intimate partner violence, and the 2010 Oxycontin reformulation

	Female Intimate Partner Violence per 100,000 people		
	(1)	(2)	(3)
Temperature (°C)	-0.0075	-0.0083***	-9.103
	(0.0051)	(0.0010)	(172.1)
Temperature × Post	0.0037	0.0083***	13.49
	(0.0032)	(0.0010)	(226.6)
Temperature × Exposure	0.0134*	0.0135***	0.0135***
	(0.0072)	(0.0013)	(0.0013)
Temperature × Exposure × Post	-0.0080*	-0.0130***	-0.0127***
	(0.0049)	(0.0013)	(0.0013)
Precipitation (m)	0.0275	0.0009	0.0040
	(0.0260)	(0.0103)	(0.0102)
Observations	31,326,025	31,326,025	31,326,025
Mean Outcome	0.05253	0.05253	0.05253
State-Month-Year FE	✓		
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Month-Year FE		✓	✓
Temperature × Year FE			✓
Jurisdiction-Location Population Weights	✓	✓	✓

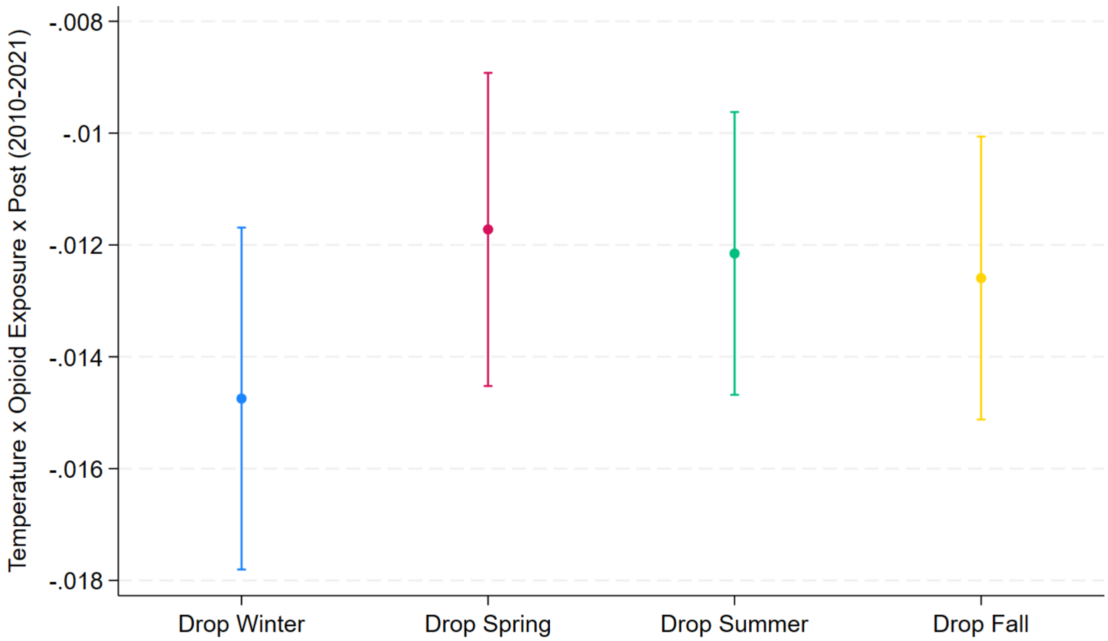
Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. *Post* is a dummy variable equal to 1 for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to opioids. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Figure A8: Triple difference (TD) of Opiod reformulation policy in 2010 on the temperature-IPV relationship (state-level clustered standard errors)



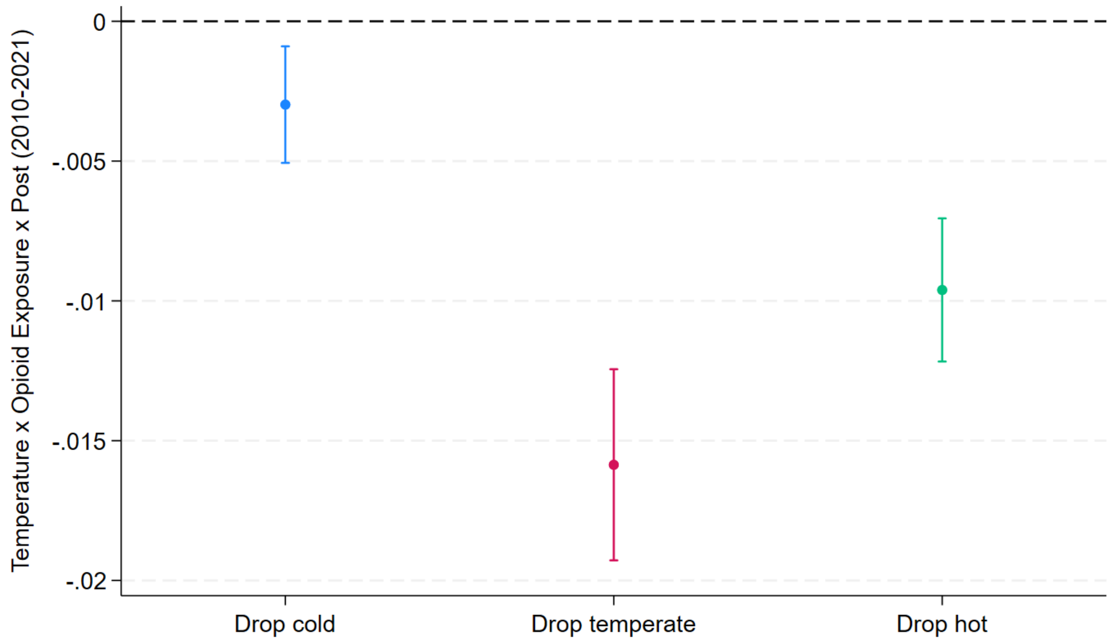
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opiod prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation 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, 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.

Figure A9: Leave-one-season-out (LOSO) triple difference of Opiod reformulation policy in 2010 on the temperature-IPV relationship



Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, a dummy post-2010, and pre-intervention exposure as the population-weighted mean per capita opiod prescription in a regression where we restrict the estimation sample leaving one season out at a time. Winter is defined as December, January, and February. Spring is defined as March, April, May. Summer is defined as June, July, August. Fall is defined as September, October, November. The regression also controls for year-specific temperature and precipitation, 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 A10: Leave-one-climate-out (LOCO) triple difference of Opiod reformulation policy in 2010 on the temperature-IPV relationship



Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, a dummy post-2010, and pre-intervention exposure as the population-weighted mean per capita opiod prescription in a regression where we restrict the estimation sample leaving counties that fall in a tercile of climate (defined from the average temperature in a county) each at a time. The regression also controls for year-specific temperature and precipitation, 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 .

Table A22: Triple difference - Aggregation

	Female Intimate Partner Violence per 100,000 people					
	Jurisdiction-Year		Jurisdiction-Month		County-Day	
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (°C)	12.42	-5.835*	-0.2224***		-0.0083***	
	(16.81)	(3.178)	(0.0386)		(0.0010)	
Temperature × Post	-10.10***	-8.327***	0.2067***		0.0083***	
	(2.091)	(1.463)	(0.0387)		(0.0010)	
Temperature × Exposure	2.877	10.25***	0.3392***	0.3366***	0.0135***	0.0135***
	(11.30)	(3.654)	(0.0283)	(0.0279)	(0.0013)	(0.0013)
Temperature × Exposure × Post	-3.289***	-2.030***	-0.3221***	-0.3172***	-0.0130***	-0.0127***
	(1.003)	(0.7399)	(0.0286)	(0.0283)	(0.0013)	(0.0013)
Precipitation (m)	-79.63***	-42.79***	0.0386	0.0260	-0.0012	0.0019
	(21.00)	(8.258)	(0.1350)	(0.1429)	(0.0097)	(0.0096)
Observations	85,764	85,764	1,029,168	1,029,168	31,320,910	31,320,910
Mean Outcome	19.1927	19.1927	1.5994	1.5994	0.05253	0.05253
County FE	✓					
Jurisdiction FE		✓				
Jurisdiction-Year FE			✓	✓		
Jurisdiction-Month-Year FE					✓	✓
Year FE	✓	✓				
Month-Year FE			✓	✓		
Week-of-Year FE					✓	✓
Day-of-Week FE					✓	✓
Temperature-Year FE				✓		✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓

Notes: The sample is respectively aggregated at the jurisdiction-year (columns 1 and 2), jurisdiction-month (columns 3 and 4) and county-day (columns 5 and 6) level. 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 prescription opioids. In columns 5 and 6 the location weights are obtained summing the population covered by all the jurisdictions in a county. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A23: Triple difference - Exposure measured using pills and shipments

	Female Intimate Partner Violence per 100,000 people	
	(1)	(2)
Temperature × Exposure (Pills)	0.00017***	
	(3.19e-05)	
Temperature × Exposure (Pills) × Post	-0.00015***	
	(3.19e-05)	
Temperature × Exposure (Shipments)		0.1314***
		(0.0118)
Temperature × Exposure (Shipments) × Post		-0.1240***
		(0.0122)
Observations	32,249,414	32,249,414
Mean Outcome	0.03582	0.03582
Jurisdiction-Month-Year FE fixed effects	✓	✓
Week-of-Year fixed effects	✓	✓
Day-of-Week fixed effects	✓	✓
Temperature × Year FE	✓	✓
Jurisdiction-Location Population Weights	✓	✓

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 A24: Triple difference - Jurisdictions with 12 months of consistent reporting

	Female Intimate Partner Violence per 100,000 people	
	(1)	(2)
Temperature (°C)	-0.0085***	
	(0.0012)	
Temperature × Post	0.0071***	
	(0.0012)	
Temperature × Exposure	0.0139***	0.0119***
	(0.0014)	(0.0012)
Temperature × Exposure × Post	-0.0109***	-0.0089***
	(0.0019)	(0.0015)
Precipitation (m)	0.0021	0.0057
	(0.0135)	(0.0116)
Observations	27,738,246	27,738,246
Mean Outcome	0.10771	0.10771
Jurisdiction-Month-Year FE	✓	✓
Week-of-Year FE	✓	✓
Day-of-Week FE	✓	✓
Temperature × Year		✓
Jurisdiction-Location Population Weights	✓	✓

Notes: The sample is restricted to the jurisdictions that report each month of the year. 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. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A25: Difference-in-difference results on IPV cases

	Female Intimate Partner Violence per 100,000 people								
	All			Heroin			Alcohol		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exposure × Post	-0.3004***	-0.3004***	-0.1955***	0.0002***	0.0002***	0.0003***	-0.0675***	-0.0675***	-0.0459***
	(0.0572)	(0.0572)	(0.0278)	(5.20e-05)	(5.20e-05)	(5.23e-05)	(0.0168)	(0.0168)	(0.0117)
Observations	25,117,587	25,117,587	25,117,587	23,105,313	23,105,313	23,105,313	25,117,587	25,117,587	25,117,587
Mean Outcome	0.03074	0.03074	0.03074	0.00001	0.00001	0.00001	0.00523	0.00523	0.00523
County FE	✓	✓		✓	✓		✓	✓	
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week-of-Year FE		✓	✓		✓	✓		✓	✓
Day-of-Week FE		✓	✓		✓	✓		✓	✓
Jurisdiction FE			✓			✓			✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The sample is restricted to the period 2006-2019. 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 prescription opioids. Standard errors are clustered at the county level. Columns 1, 4 and 7 use the same fixed effects as Dave et al. (2023). Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A26: Triple difference - Heterogeneity by County Characteristics

	Female Intimate Partner Violence per 100,000 people			
	Urban/Rural		High School Education	
	Urban	Rural	Below median	Above median
	(1)	(2)	(3)	(4)
Panel A: Urbanization and Education				
Temperature × Exposure	0.00665***	0.0102***	0.0200***	0.00283**
	(0.00174)	(0.00119)	(0.00229)	(0.00113)
Temperature × Exposure × Post	-0.00578***	-0.00936***	-0.0194***	-0.00154
	(0.00178)	(0.00127)	(0.00227)	(0.00115)
Observations	10,920,860	20,405,165	15,665,977	15,660,048
Mean Outcome	1.042	0.024	0.054	0.980
	Income		Labor Force Participation	
	Below median	Above median	Below median	Above median
	(5)	(6)	(7)	(8)
Panel B: Economic Stress				
Temperature × Exposure	0.0193***	0.00236**	0.000898	0.0166***
	(0.00264)	(0.00119)	(0.00134)	(0.00195)
Temperature × Exposure × Post	-0.0190***	-0.00141	-0.000554	-0.0162***
	(0.00260)	(0.00116)	(0.00122)	(0.00192)
Observations	15,668,877	15,657,148	13,932,925	17,393,100
Mean Outcome	0.480	2.827	2.691	0.442
Temperature-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *Post* is a dummy variable equal to one for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to prescription opioids. Mean and standard deviation of the outcome are computed in the pre-policy sample. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A27: Triple difference - Heterogeneity by Type of Offense

	Female Intimate Partner Violence per 100,000 people					
	All	Assault	Rape	Murder	No-firearm	Firearm
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × Exposure	0.0137***	0.0133***	0.000137**	0.0000316	0.0119***	0.000234**
	(0.00132)	(0.00127)	(0.0000678)	(0.0000251)	(0.00112)	(0.0000910)
Temperature × Exposure × Post	-0.0129***	-0.0126***	-0.000123*	-0.0000325	-0.0113***	-0.000222**
	(0.00135)	(0.00130)	(0.0000678)	(0.0000253)	(0.00114)	(0.0000916)
Observations	31326025	31326025	31326025	31326025	31031847	31031847
Mean Outcome	0.077	0.075	0.001	0.000	0.064	0.001
Temperature-Year FE	✓	✓	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓	✓

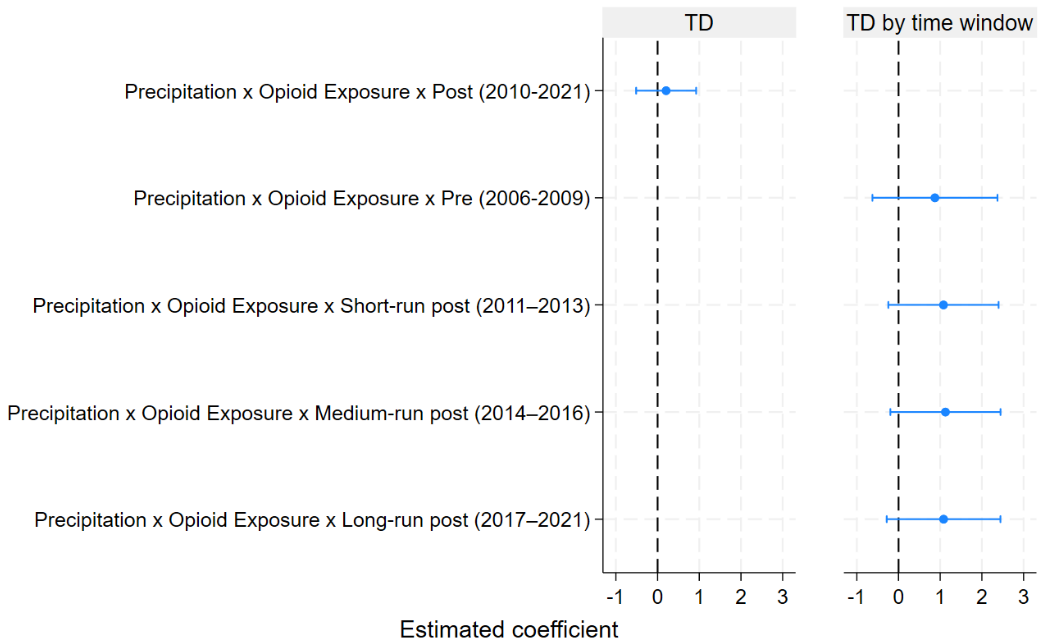
Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *Post* is a dummy variable equal to one for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to prescription opioids. Mean and standard deviation of the outcome are computed in the pre-policy sample. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A28: Triple difference - Heterogeneity by Time of the Day

	Female Intimate Partner Violence per 100,000 people			
	Morning	Afternoon	Evening	Night
	(1)	(2)	(3)	(4)
Temperature × Exposure	0.00124***	0.00230***	0.00596***	0.00409***
	(0.000230)	(0.000374)	(0.000595)	(0.000432)
Temperature × Exposure × Post	-0.00111***	-0.00214***	-0.00570***	-0.00390***
	(0.000236)	(0.000381)	(0.000594)	(0.000433)
Observations	31,288,794	31,288,794	31,288,794	31,288,794
Mean Outcome	0.012	0.018	0.027	0.018
Temperature-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *Post* is a dummy variable equal to one for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to prescription opioids. We count the number of IPV cases and compute temperature from hourly data during the "Morning" (6:00am to 11:59am), "Afternoon" (12:00pm to 5:59pm), "Evening" (6:00pm to 11:59pm), and "Night" (12:00am to 5:59am). Mean and standard deviation of the outcome are computed in the pre-policy sample. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Figure A11: Triple difference (TD) of Opiod reformulation policy in 2010 on the precipitation-IPV relationship



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

Table A29: Triple difference - Heterogeneity by Location of the Crime

	Female IPV per 100,000 people		
	All	Inside	Outside
	(1)	(2)	(3)
Temperature × Exposure	0.0137***	0.00324***	0.0102***
	(0.00132)	(0.000402)	(0.000989)
Temperature × Exposure × Post	-0.0129***	-0.00306***	-0.00966***
	(0.00135)	(0.000403)	(0.00101)
Observations	31,326,025	31,326,025	31,326,025
Mean Outcome	0.077	0.014	0.062
Temperature-Year FE	✓	✓	✓
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *Post* is a dummy variable equal to one for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to prescription opioids. Mean and standard deviation of the outcome are computed in the pre-policy sample. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

Table A30: Triple difference - Heterogeneity by Distance from US-Mexico border crossings

	Female Intimate Partner Violence per 100,000 people		
	US-Mexico Closest Border Crossing Distance		
	Interaction	Below Median	Above Median
	(1)	(2)	(3)
Temperature × Exposure	-0.000365	0.00815***	0.0113***
	(0.00384)	(0.00128)	(0.00146)
Temperature × Exposure × Post	-0.000631	-0.00760***	-0.00997***
	(0.00388)	(0.00127)	(0.00156)
Temperature × Distance	-0.00000764***		
	(0.00000142)		
Temperature × Distance × Post	0.00000680***		
	(0.00000147)		
Temperature × Exposure × Distance	0.00000411*		
	(0.00000215)		
Temperature × Exposure × Distance × Post	-0.00000312		
	(0.00000219)		
Observations	31,305,571	14,992,163	16,333,862
Mean Outcome	0.076	1.089	0.044
Temperature-Year FE	✓	✓	✓
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
Jurisdiction-Month-Year FE	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence on females per 100,000 people. Temperature is the average daily temperature measured in degrees Celsius (°C). *Post* is a dummy variable equal to one for the post-reformulation period, starting from 2010. *Exposure* is the county-level pre-2010 exposure to prescription opioids. *Distance* is the distance from the population centroid of each county to the geographic coordinates of the nearest US-Mexico border crossing. In columns 2-3, we split the sample by counties above/below the sample median of distance. Standard errors are clustered at the county level. Significance levels are indicated as follows: *p<0.10, ** p<0.05, *** p<0.01.

A.2.4 Mechanisms: Robustness

Table A31: 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 A32: 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 A33: 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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.