Cooling the Heat: Co-benefits of Opioid-reformulation on Temperature and Intimate Partner Violence

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Abstract

Intimate Partner Violence (IPV) is a major public health issue often associated with substance abuse. Building on burgeoning prior work showing that higher temperatures increase violent behavior, we document a strong positive effect of temperatures on IPV cases on female victims in the United States using administrative daily data over thirty years at the jurisdiction level. Combining an exogenous abuse-deterrent reformulation of opioids with random variation in daily temperature, we examine whether reducing prescription opioid misuse exacerbates or mitigates the effect of temperature on IPV. Using a within-county triple difference and an event study design, we document that the reformulation significantly mitigates the temperature-IPV gradient in the short-run in counties with greater initial rates of prescription opioid usage. The effect of the policy is more pronounced in urban and richer counties, explaining disparities in IPV outcomes across racial and ethnic groups.

Keywords: Intimate Partner Violence, Temperature, Opioid

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 indicated as a factor facilitating IPV (Stone and Rothman, 2019; Radcliffe 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 policies designed to curtail prescription opioid misuse mitigate or exacerbate this effect. 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 - a supply-side intervention that addresses the over-prescription of opioids and mitigates their addictive risks. We combine these two sources of county-level variation in a triple-difference and event-study research designs, 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 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. Combining weather variation with county-level variation in exposure to prescription opioids, the triple-difference estimates reveal that a 1°C increase is associated with 0.008 fewer IPV cases per 100,000 people after the opioid reformulation ($\approx$ 7.9% decrease at the mean) in counties with greater baseline exposure to opioids. The event-study analysis documents that the attenuating role of the policy does not last more than five years after the policy. Altogether these results suggest a positive unintended co-benefit of the opioid reformulating in mitigating the role of temperature in inducing violent behavior and increases in intimate partner violence.

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 additional results on the mediating role of the policy environment contribute to the growing literature on the (un)intended consequences of policies in mediating or exacerbating climate impacts on socio-economic outcomes. Health care policies have been shown to attenuate the temperature-mortality relationship in the US (Mullins and White, 2020) and in Mexico (Cohen and Dechezleprêtre, 2022). More restrictive gun laws attenuate the temperature-homicide relationship (Colmer and Doleac, 2023). Cash transfers also attenuate the effects of higher temperatures on violent behavior, but only temporarily (Garg et al., 2020).[1] Our study is the first one that examines the positive externality 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)

[1]Policies, however, 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).

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 evidence on the mediating role of the opioid reformulation. We examine the mechanisms and uncover substantial heterogeneity across sub-populations where the policy was effective, underlining the importance of identifying subgroups of population where the temperature-IPV gradient is positive and inelastic to policy interventions. In particular, we document that the policy was not effective in marginalised communities, including rural, low-income, high-poverty, non-Hispanic, non-White, Black counties.

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. (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 (Mullins and White, 2019), increasing anxiety, despair and isolation, which can in turn exacerbate substance use. 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 (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]

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, particularly so if other therapeutic substitutes, such as medical marijuana, are not available. On the other hand, supply-side interventions could reduce the overall pool of addicts, reducing crime. Which of the two mechanisms prevails is

[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.

an empirical question that we address in this paper.

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]

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

[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.

[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 can relax their data restrictions.

tion for the representative individual in the county.[5] Although the IPV data are originally at the jurisdiction level, geographical coordinates are not available at 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 explore in subsequent analysis the finer original temporal resolution of the data (hourly).[6] In particular, we compute population-weighted daily maximum, minimum, and nighttime temperature.[7]

2.2.3 Opioid use

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

[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).

[6] In future versions of this work, we aim at replicating the analysis using the PRISM data to check for the robustness of the results.

[7] Nighttime temperature is defined in three alternative ways: we consider the average temperature i) between 6pm and 6am; ii) between 8pm and 6am, iii) between 8pm and 8am.

difficult to crush or dissolve. The version was approved by the Food and Drug Administration in 2010, which became effective immediately with the new formulation being distributed and the previous formulation being discontinued (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) (Evans et al., 2022). 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.

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.[8]

[8] In the future version of this work, which will be available for the conference, we are going to explore further mechanisms on the relationship between IPV and temperature. This includes the

Medical marijuana laws. We explore the substitution/complementary role of legal marijuana on access restrictions to opioids. Legal marijuana reduce 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. We test for this hypothesis in Section 5.

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.[9]

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.

role of alcohol consumption and mental health, happiness, and well-being using the Behavioral Risk Factor Surveillance System (BRFSS) survey, and potential temperature-induced changes in time-use as measured in the American Time Use Survey (ATUS).

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

Table 1 provides summary statistics on the main variables of interest. On average, in our sample period 0.06 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. Using data from Centers for Disease Control (CDC), the population-weighted mean number of all Schedule II opioid prescriptions per capita in the county for the period 2006 to 2009 is centered at 0.89 prescriptions. As for weather variables, in the whole sample the average daily temperature and total daily precipitation are 11.09 °C and 0.003 metres, respectively.

Table 1: Descriptive Statistics

	1991-2021		1991-2009		2010-2021	
	Mean	SD	Mean	SD	Mean	SD
NBRIS						
IPV on female per 100,000 people	0.06	0.59	0.08	0.72	0.05	0.52
Opioid use						
Per capita opioid prescriptions			0.89	0.35		
ERA5-Land						
Average daily temperature (°C)	11.09	10.50	9.46	10.13	11.88	10.58
Total daily precipitation (m)	0.00	0.01	0.00	0.01	0.00	0.01
Observations	44,170,732		26,425,814		17,744,918	

Notes: NBRIS descriptive statistics are weighted by jurisdiction-location population. The figures for per capita opioid prescriptions refer to the period 2006-2009.

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.[10]

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.

[10] 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).

3.2 Results

Table 2 reports the results from the estimation of Equation 1. Column (1) displays the unconditional estimate of the relationship between the number of intimate partner violence cases per 100,000 people and daily realizations of temperature and precipitation. We find that, on average, a one-degree Celsius increase in average daily temperature is associated with an increase by 0.009 more cases of intimate partner violence per 100,000 people. This corresponds to a 1.34% increase with respect to the mean. Moreover, we find that precipitation is also associated with an increase in cases of intimate partner violence.

In Columns (2)-(3), we exploit month-year and county-month-year variation to identify the relationship temperature-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 0.0107-0.0221 more cases of intimate partner violence per 100,000 people, corresponding to a 1.60%-3.30% increase with respect to the mean. The effect of precipitation is not robust to the inclusion of county-month-year fixed effects.

Columns (4)-(5) replace county-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 (6) 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 (≈ 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 (Table A1); trimming the sample (Table A2); expressing the dependent variable as count variable (Table A3); testing alternative fixed-effects (Table A4), and standard errors clustered at the state level (Table A5). We also explore non-linear specifications of temperature, using 5-degree temperature bins (Figure A3, Table A6), share of hours in a day in a temperature bin (Table A7), and a up to 4-degree polynomial (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 (Table A9). We observe displacement effects offsetting nearly 60 percent of the contemporaneous effect after 21 days.[11] Finally, we also restrict our attention to temperatures over night to examine whether sleep deprivation could

[11] 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 $d-1$.

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 (Table A10). We set out to further explore this mechanism in Section 5.

Table 2: Temperature and Intimate Partner Violence

	Intimate Partner Violence per 100,000 people					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (°C)	0.0090***	0.0221***	0.0107***	0.0040***	0.0058***	0.0005**
	(0.0006)	(0.0018)	(0.0010)	(0.0002)	(0.0003)	(0.0002)
Precipitation (m)	0.6838***	1.464***	0.3675	-0.3330*	-0.0232	-0.0126
	(0.2552)	(0.2831)	(0.2368)	(0.1883)	(0.2146)	(0.0101)
Observations	44,170,732	44,170,732	44,170,732	44,170,732	44,170,732	44,170,732
Dependent Variable Mean	0.66975	0.66975	0.66975	0.66975	0.66975	0.05741
Month-Year FE		✓				
Week-of-Year FE		✓	✓	✓	✓	✓
Day-of-Week FE		✓	✓	✓	✓	✓
County-Month-Year FE			✓			
Jurisdiction FE				✓		
Jurisdiction-Month-Year FE					✓	✓
Jurisdiction-Location Population Weights						✓

Notes: The dependent variable is the number of intimate partner violence 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.

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.

Offenses. First, we test whether temperature only affects specific offenses within the IPV domain. 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, 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. 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 (9:00pm to 11:59pm), and night (12:00am to 5:59am). 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 at home, 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. 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.

County-level socio-demographic characteristics. Finally, we test for the presence of heterogeneous effects across socio-demographic characteristics at the county-level.[12] Table A16 reports the estimates for each socio-demographic dimension. First, in Column (1) we test the urban-rural divide, defining a jurisdiction 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 effect or changes in social interactions during hot days.[13]

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.

[12] 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}.

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

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.

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 (Table A17) 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 (DiDiD) specification which exploits within-county changes in opioid reformulation alongside with within-county variation in temperature over time. We estimate the following specification:

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

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. In an alternative specification, we allow for heterogeneous effects of OxyContin reformulation and estimate differential impacts by time window after the policy 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).

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 an event study specification where the interaction term between daily temperature and pre-2010 exposure to prescription opioids is 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.

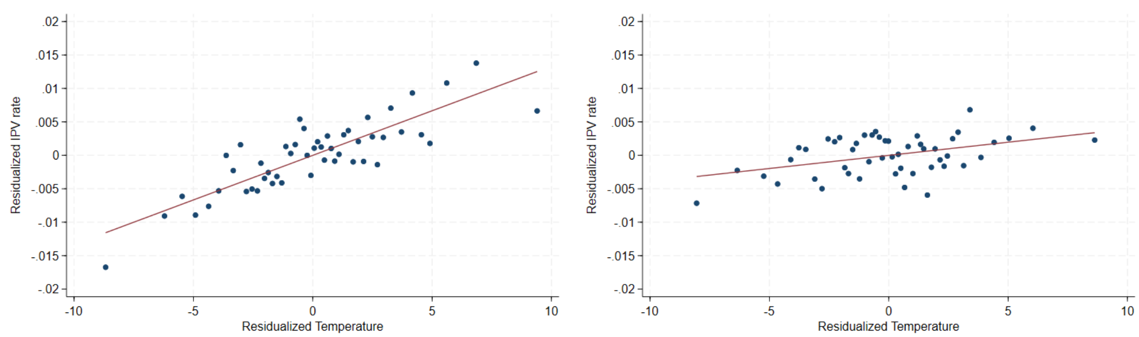
We estimate Equation (2) using weighted-least squares where the weights are the average population in the jurisdiction during the sample period. Standard errors are clustered at the county-level.

4.2 Results

To explore the potential moderating or exacerbating role of the opioid reformulation, Figure 1 shows the regression-adjusted relationship between temperature and intimate partner violence cases separately in a sample after the policy reformulation with low opioid prescriptions in Panel A and high opioid prescriptions in Panel B. We determine each group using the median opioid prescription (1.02) sample split. The relationship between temperature and IPV is positive in both panels, confirming our previous result that higher temperature increases IPV cases. In counties where opioid prescriptions per capita are high, however, the slope of the positive gradient reduces dramatically and is not statistically different than zero at conventional levels. 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.

Figure 1: Temperature and Opioid prescription reformulation

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



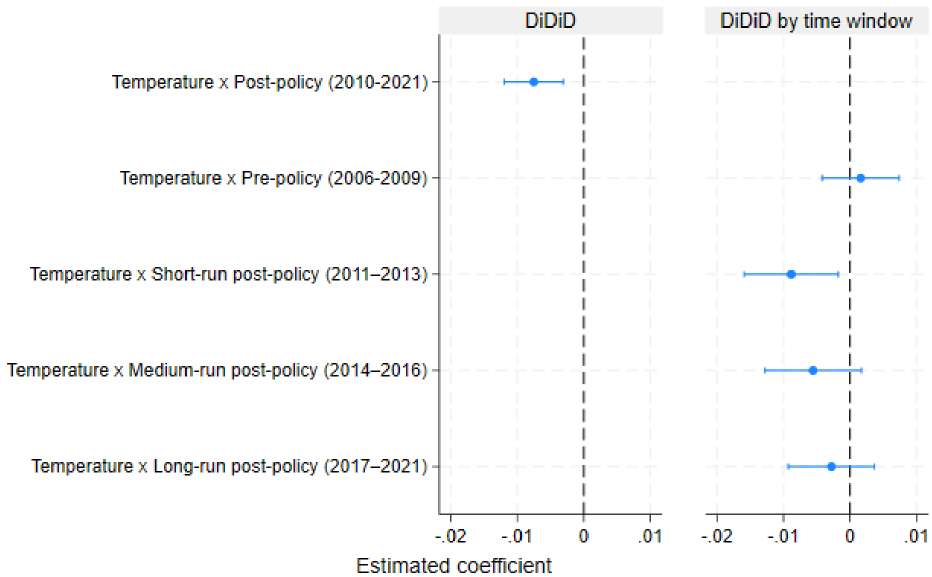
Notes: Panels (a) and (b) show binned scatterplots with 50 bins and a linear regression on the underlying data. Each shows the correlation net of jurisdiction-month-year, week-of-year, day-of-week fixed effects between residualized IPV rate and residualized temperature. The panels show the relationship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

To provide further evidence on the role of the opioid reformulation, Figure 2 displays the results from the triple difference (DiDiD) research design. The graph on the left-hand side reports the coefficient associated with the triple interaction term, which is negative and statistically significant. We find that a 1°C increase in temperature is associated with 0.008 fewer IPV cases per 100,000 people after the reformulation occurred in 2010, a 7.9% reduction at the mean. Compared to our baseline estimate of the temperature-IPV relationship (0.0005/1°C, in column 6, Table 2), the results suggest that the opioid reformulation strongly attenuates the temperature-IPV relationship.

On the right-hand side of Figure 2, we explore the hypothesis that the attenuation role of OxyContin's reformulation in the temperature-IPV relationship varies over time since the implementation of the policy. We consider short-run, medium-run, and long-run impacts of the policy by estimating four different triple interaction terms that also include the pre-policy period. The triple interaction term with the time indicator of the pre-policy period is small in magnitude and not statistically significant at conventional levels, allaying concerns on differential pre-intervention trends between high- and low-exposure counties to prescription opioids. In the post-policy period, the triple interaction term is negative and statistically significant at the 95% level only for the years immediately following reformulation (2011 to 2013). The coefficient is similar in magnitude to the baseline triple difference estimate: a 1°C increase in temperature is associated with 0.007 fewer IPV cases per 100,000 people after the reformulation occurred in 2010. The effect fades away for several years post-reformulation suggesting that the attenuation role of opioid reformulation is only temporary.

Our results are robust to a variety of alternative specifications that: use alternative fixed effects, accounting for jurisdiction-day, jurisdiction-month-year, and date fixed effects (Appendix Figure A5); exclude the Covid-19 period after 2019 (Appendix Figure A6); account for wyear-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).

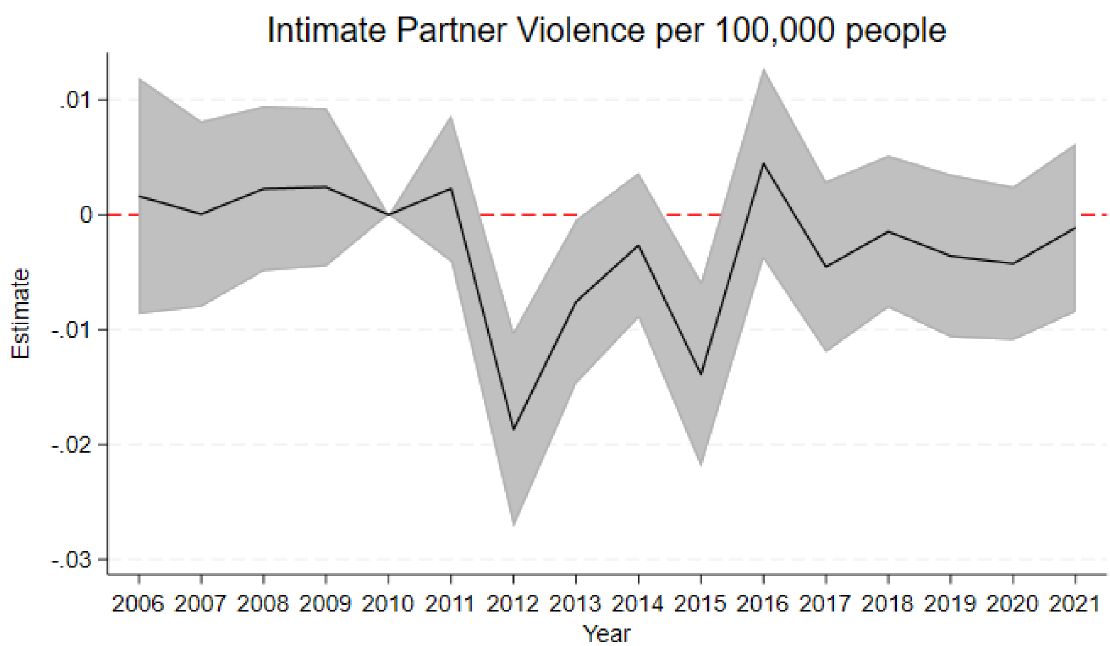
Figure 2: Triple difference (DiDiD) of Opiod reformulation policy in 2010 on the temperature-IPV relationship



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.

Figure 3 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. The estimated coefficients in the years prior to reformulation are statistically indistinguishable from zero, consistent with no temperature differences between higher- and lower-exposure counties during the pre-reformulation period. 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 0.005 IPV cases per 100,000 people/1°C/day. The policy-induced attenuation of the temperature effect is persistent up to 5 years after the policy change and fades away after 2015, consistent with the short-run effect highlighted in the triple difference findings.

Figure 3: 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 additional results that provide insights into the channels through which opioid reformulation attenuates the temperature-IPV relationship.

We begin by documenting how the attenuation effect of opioid reformulation on the temperature-IPV gradient is heterogeneous across socio-economic characteristics at the county-level. We estimate a quadruple interaction terms that combines temperature, pre-policy opioid exposure, a post-policy time indicator and an indicator that categorizes counties above and below the sample median in terms of urban/rural, unemployment levels, pre-dominant ethnic groups (White, Black, Hispanic), income and poverty measures. Figure 4 displays the coefficient on the quadruple interaction term for each socio-demographic margin considered. Although there is meaningful overlap in the confidence intervals across sub-groups of population studied, we discuss in detail below some evidence of the heterogeneous impacts of the policy.

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 test for which of these two mechanisms prevails and show that the policy is effective only in urban areas. Opioid reformulation mitigates the temperature-IPV gradient in urban areas, in contrast with previous temperature-homicide studies that document the effect to be attenuated by gun law restrictions only in rural areas (Colmer and Doleac, 2023). A potential explanation behind this finding is that higher temperatures can halt addiction treatment programs and derail critical medication supply chains, more so in rural areas, where fewer health-care providers are available, and patients often need to travel substantial distances to receive care.

Economic stress. Higher unemployment rates often lead to increased economic stress and hardship in communities. Individuals facing economic difficulties may be more susceptible to substance abuse as a coping mechanism. We document that the opioid reformulation is effective at mitigating the effect of temperature on IPV only in counties with unemployment rate above the median. This result seems at first in contrast with additional heterogeneous impacts of the policy that, although imprecisely, suggest that the policy is effective in richer counties with lower poverty rates. We explain this contrast with greater access to alternative coping mechanisms in richer counties, such as mental health services, recreational activities, and community support. This could reduce the reliance on opioids as a coping mechanism for stress and pain. In these counties, the policy might reinforce existing support systems. Moreover, opioid abuse can have different socioeconomic drivers. In certain cases, unemployment might be a significant factor, while in richer counties, it could be related to other factors, including stress, mental health, or over-prescription.

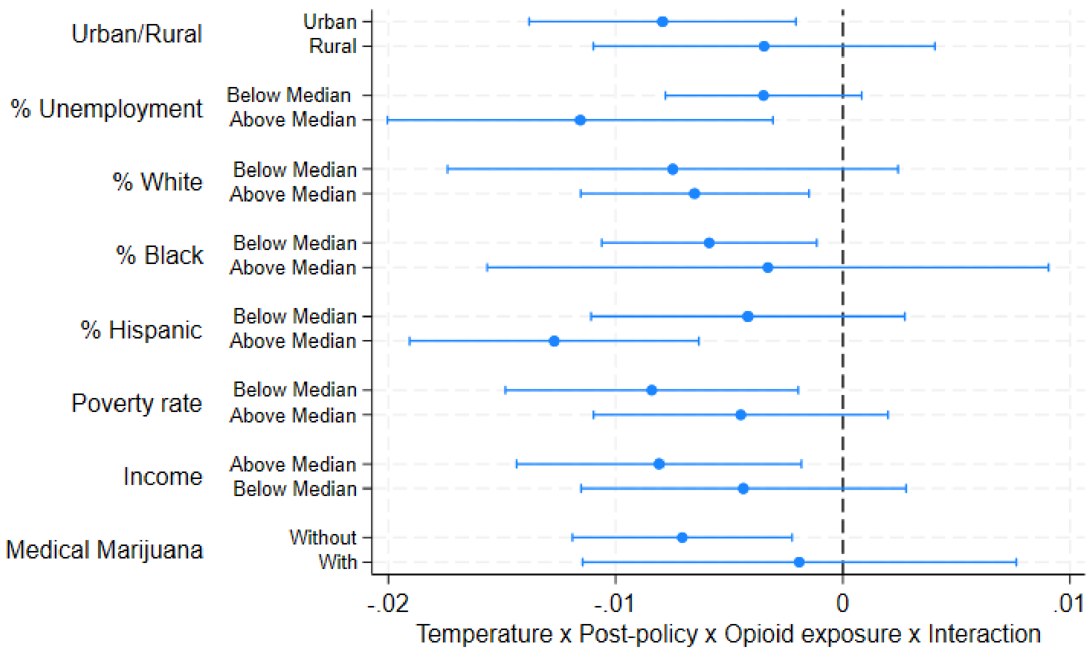
Environmental justice. The impact of the opioid prescription reformulation policy exhibits heterogeneity across counties with varying racial demographics, emphasizing the intersectionality of environmental justice concerns (Banzhaf et al., 2019). In counties with predominantly white populations and below-median black population, the policy is effective at mitigating the effect of temperature due to potentially higher access to healthcare resources. In contrast, counties with larger Hispanic populations may face unique challenges such as language barriers and disparities in healthcare access, influencing the policy's efficacy differently. Understanding these variations is crucial for ensuring environmental justice, as vulnerable communities may experience different levels of protection and support.

Medical Marijuana Laws. Last, we test for the extent to which 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. In areas where medical marijuana is legally accessible, people may choose to substitute opioids with marijuana, potentially reducing the likelihood of turning to more destructive and uncontrolled substances such as heroin. Although associative, these results suggest that access to marijuana dampens the substitution to more destructive and uncontrolled substances and also mutes the co-benefits of the opioid reformulation on the effect of temperatures.

Type of offense. We examine if the policy is effective at mitigating certain types of IPV offenses caused by temperature. Figure A11 displays the percentage change in IPV with respect to the pre-policy mean. Our results indicate that the supply shock in opioid availability reduces IPV cases that involve assault (0.7%), while the effect is not significant on murder and rape 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. Finally, the effect is larger for outside IPV cases, but not statistically different than inside IPV cases.

Sleep deprivation. Healthy sleep is an important aspect of successfully treating opioid use disorders. Opioid abuse damages sleep duration and quality (Bertz et al., 2019). At the same time, increases in nighttime temperatures can amplify nights of insufficient sleep and deteriorate sleep quality (Minor et al., 2022; Obradovich

Figure 4: Heterogeneous effect of the Opiod reformulation on the temperature-IPV relationship



Notes: The figure plots the coefficients associated with the quadruple interaction term between daily-temperature, pre-intervention opioid exposure, post-2010 dummy, and each population subgroup/county type 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. Bins area represent the 95% confidence intervals with standard errors clustered at the county-level.

et al., 2017), which in turn, 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 this channel by using a measure of nighttime temperature (Appendix Table A18). We document that, although nighttime temperature has a positive significant effect on IPV, the effect is attenuated after the reformulation in counties with higher exposure to opioid prescription. This result suggests that the negative supply-side shock induced by the policy can help improve sleep duration and quality and moderate the compounding effect of violence induced by opioid abuse and warmer nighttime temperature.

Social interactions. Intimate partner violence is a crime that more often occurs at home rather than 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 the precipitation-IPV relationship (Appendix Figure A12) and document an effect that is not significant at any conventional level. This result suggests that on opioid reformulation does not affect IPV offenses that are sensitive to precipitation, i.e., that arise in contexts with greater social interaction.[14]

6 Discussion and conclusions

Our study contributes to understanding how warmer temperature may lead to a higher incidence of female victims of intimate partner violence. We address this question in the United States using administrative daily-level data over the past three decades to test for the effect the impact of higher temperatures on IPV perpetration on females in the United States, and to examine the moderating effect of policies targeting prescription opioid misuse.

We 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. The policy has been particularly effective in urban and richer counties, and where potential substitutes

[14]In the future version of the manuscript, we plan to explore how our estimates vary between locations of crime (at home, outside, other location) to further disentangle the potential social channel.

like marijuana are not legally available. 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, indicating a 7.9% reduction in IPV cases per 100,000 people for every one-degree Celsius temperature increase in high opioid exposure counties. The event-study analysis suggests that the policy's moderating effect diminishes after five years.

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. We estimate that, on average, after OxyContin reformulation one-degree Celsius increase is associated with 2,828 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 \$383.307 million (in \$2023) for one-degree Celsius increase in average daily temperature.[15]

This expected social benefit is economically meaningful. To illustrate, it is equivalent to the establishment of 42 additional Substance Abuse Treatment Facilities facilities (Bondurant et al., 2018),[16] and 727 new mental healthcare facilities (Deza et al., 2022).[17] Moreover, it has also reduced the economic burden associ-

[15] This is obtained as follows: -0.008 IPV cases per 100,000 people $\times$ 365 (days) $\times$ Average population between 2006-2009 $\times$ 0.32 (opioid prescription interquartile range) $\times$ \$135,556 (lifetime cost of an IPV case) $\times$ 1 (degree Celsius change in temperature).

[16] 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).

[17] 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.

ated 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 2 years of funding for the Comprehensive Addiction and Recovery Act (CARA),[18], 12% of the budget for the Violence Against Women Act (VAWA),[19] and 7 supplemental funding allocations to the Family Violence Prevention and Services Act (FVPSA).[20] This back-to-the-envelope estimate highlights the substantial beneficial welfare-enhancing role of 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.

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[18]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.

[19]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.

[20]The Coronavirus Aid, Relief, and Economic Security (CARES) Act included $52.99 million (in $2023) of supplemental funding to address DV under the 1984 Family Violence Prevention and Services Act Program.

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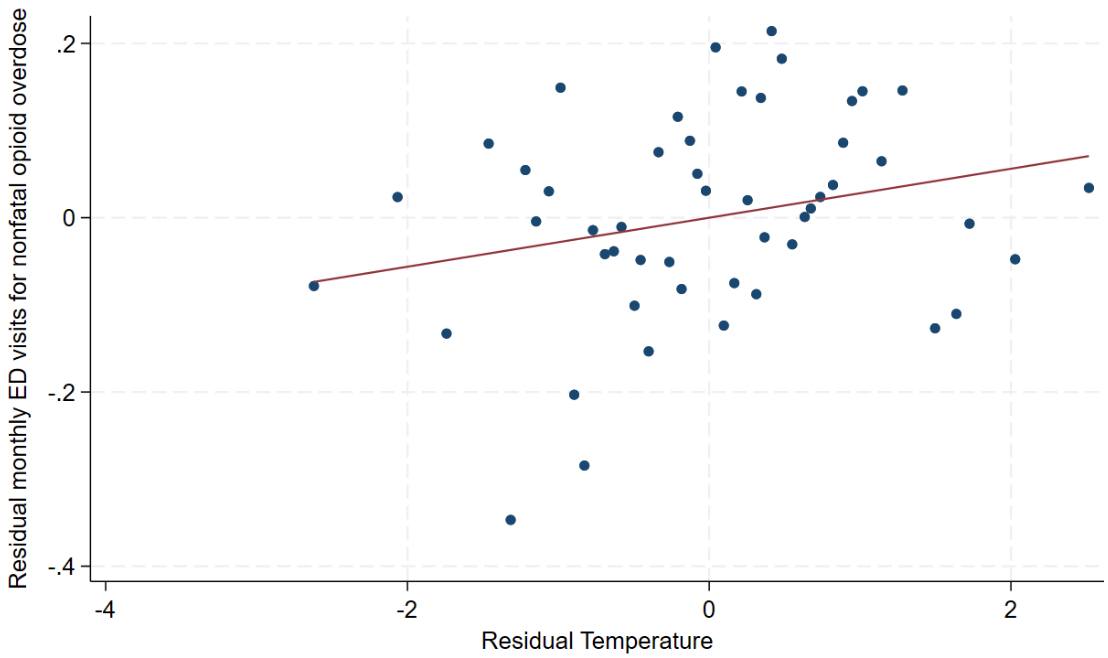
A Online Appendix

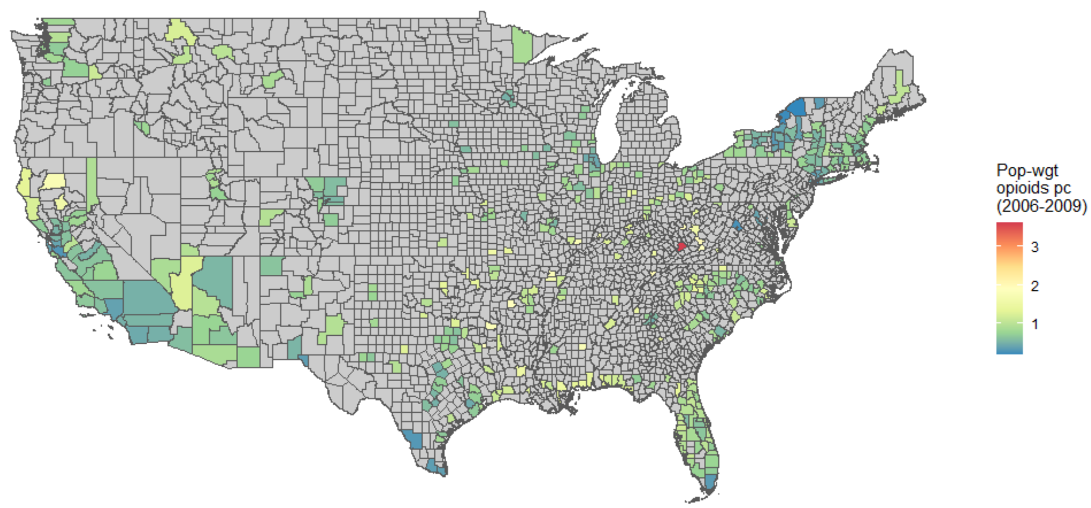
A.1 Additional Figures

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 341 counties as reported in Evans et al. (2022). Sample mean is 0.89, standard deviation is 0.35.

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

	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
	(0.0090)	(0.0101)
Observations	37,687,828	44,170,732
Dependent variable mean	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 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

	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)	(9.31e-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
Dependent variable mean	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 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

	# Intimate Partner Violence		
	OLS	PPML	PPML
	(1)	(2)	(3)
Temperature (°C)	0.0011***	0.0185***	0.0104***
	(0.0004)	(0.0035)	(0.0016)
Precipitation (m)	-0.0279	0.1790	-0.1017
	(0.0560)	(0.4844)	(0.3538)
Observations	44,170,732	40,613,425	23,638,551
Dependent Variable Mean	0.11771	0.11771	0.11771
Week-of-Year FE	✓	✓	✓
Day-of-Week FE	✓	✓	✓
County-Month-Year FE		✓	
Jurisdiction-Month-Year FE	✓		✓
Jurisdiction-Location Population Weights	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence cases. 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

	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
	(0.0101)	(0.0264)	(0.0174)	(0.0154)
Cumulative Effect of Temperature				0.0003***
				(0.0001)
Cumulative Effect of All Temperature Leads				0.000259**
				(0.000106)
Cumulative Effect of 2nd to 7th Temperature Leads				-1.71e-05
				(4.97e-05)
Observations	44,170,732	44,170,732	44,170,732	43,979,205
Dependent Variable Mean	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	✓	✓	✓	✓

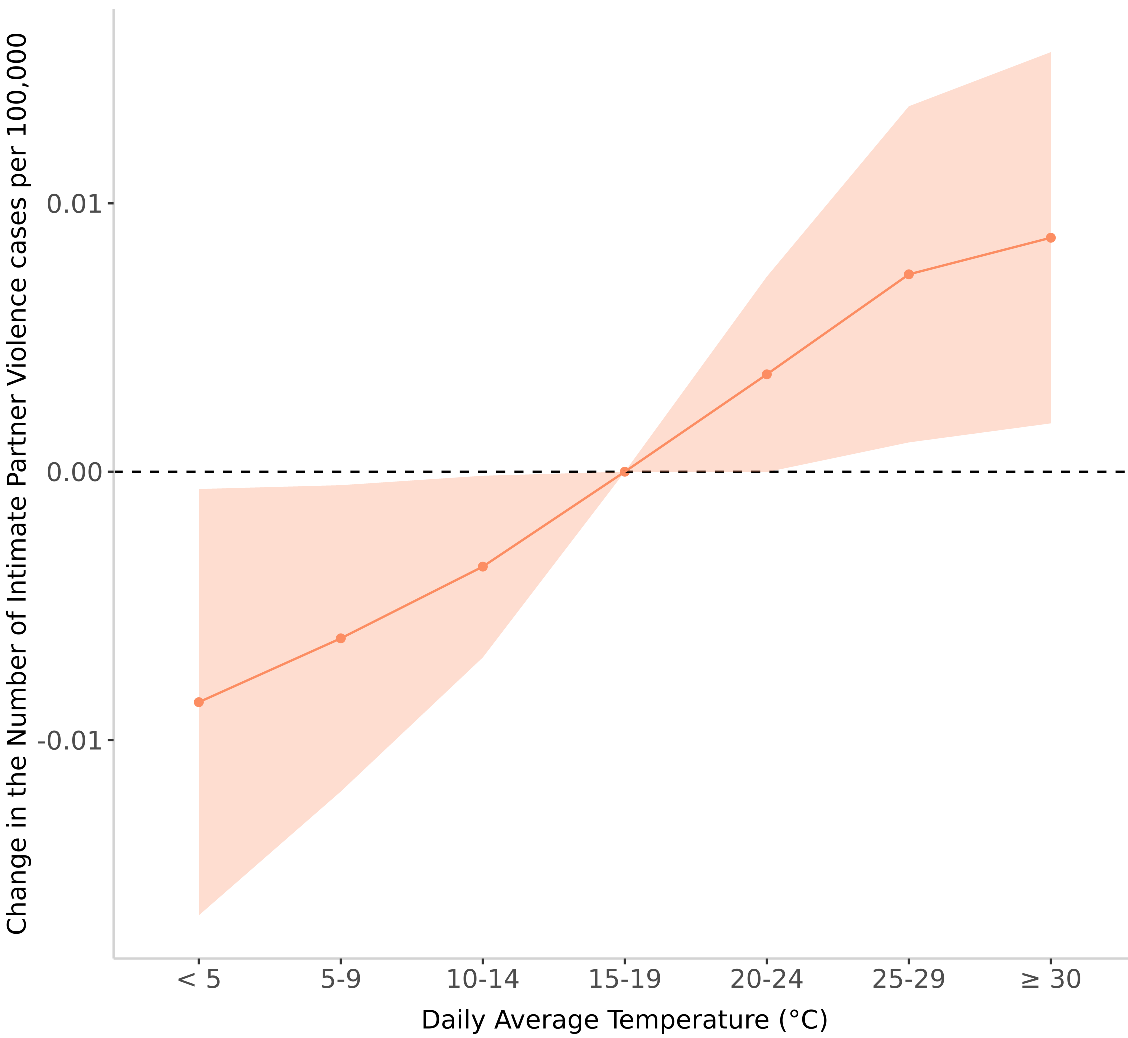
Notes: The dependent variable is the number of intimate partner violence per 100,000 people. Column (1) reports the baseline results. In Columns (3) and (4) we use the same fixed effect specification from Cohen et al. (2018). In Column (4) we also control for 7-day lags and leads. In the same column 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

	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
	(0.0101)	(0.0116)
Observations	44,170,732	44,170,732
Dependent Variable Mean	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 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 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

	Intimate Partner Violence per 100,000 people				
	(1)	(2)	(3)	(4)	(5)
< 5 (°C)	-0.0189**	-0.0958***	-0.0177**	-0.0046	-0.0086**
	(0.0074)	(0.0298)	(0.0083)	(0.0032)	(0.0040)
5-10 (°C)	-0.0027	-0.0582***	-0.0121**	-0.0051**	-0.0062**
	(0.0021)	(0.0168)	(0.0056)	(0.0025)	(0.0029)
10-15 (°C)	-0.0027	-0.0312***	-0.0066**	-0.0037**	-0.0035**
	(0.0021)	(0.0087)	(0.0030)	(0.0016)	(0.0017)
20-25 (°C)	0.0095**	0.0379***	0.0069*	0.0044***	0.0036*
	(0.0042)	(0.0143)	(0.0037)	(0.0017)	(0.0019)
25-30 (°C)	0.0556***	0.0988***	0.0162**	0.0099***	0.0074**
	(0.0190)	(0.0311)	(0.0073)	(0.0029)	(0.0032)
$\geq$ 30 (°C)	0.0933*	0.1379***	0.0211***	0.0133**	0.0087**
	(0.0522)	(0.0409)	(0.0080)	(0.0055)	(0.0035)
Precipitation (m)	0.1018	0.0956	0.0443	-0.0151	-0.0002
	(0.1619)	(0.1018)	(0.0340)	(0.0180)	(0.0103)
Observations	44,170,732	44,170,732	44,170,732	44,170,732	44,170,732
Dependent Variable Mean	0.05741	0.05741	0.05741	0.05741	0.05741
Month-Year FE		✓			
Week-of-Year FE		✓	✓	✓	✓
Day-of-Week FE		✓	✓	✓	✓
County-Month-Year FE			✓		
Jurisdiction FE				✓	
Jurisdiction-Month-Year FE					✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence 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

	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
Dependent Variable Mean	0.05741	0.05741	0.05741	0.05741	0.05741
Month-Year FE		✓			
Week-of-Year FE		✓	✓	✓	✓
Day-of-Week FE		✓	✓	✓	✓
County-Month-Year FE			✓		
Jurisdiction FE				✓	
Jurisdiction-Month-Year FE					✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓	✓

Notes: The dependent variable is the number of intimate partner violence 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)

	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**
		(6.03e-06)	(6.59e-06)	(8.61e-06)
Temperature^3			3.11e-08	2.43e-07
			(9.65e-08)	(1.52e-07)
Temperature^4				-8.85e-09
				(7.58e-09)
Precipitation (m)	-0.0126	0.0058	0.0060	0.0064
	(0.0101)	(0.0129)	(0.0126)	(0.0127)
Observations	44,170,732	44,170,732	44,170,732	44,170,732
Dependent Variable Mean	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 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

	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)	(0.0103)	(0.0120)	(0.0108)
Cumulative Effect of Temperature	0.0003**	0.0002**	0.0002*		0.0002*
	(0.0001)	(9.41e-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	-1.23e-05
				(4.84e-05)	(2.31e-05)
Observations	44,074,951	43,979,170	43,883,389	44,074,986	43,979,205
Dependent variable mean	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 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

	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)
Nighttime	6pm-6am	8pm-6am	8pm-8am
R^2	0.252	0.252	0.252
Observations	44,170,732	44,170,732	44,170,732
Dependent Variable Mean	0.0574	0.0574	0.0574
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 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: Heterogeneity — Offenses

	Intimate Partner Violence per 100,000 people		
	Assault	Rape	Murder
	(1)	(2)	(3)
Temperature (°C)	0.0005**	4.53e-06*	-5.91e-08
	(0.0002)	(2.63e-06)	(2.36e-07)
Precipitation (m)	-0.0121	-0.0003	-0.0121
	(0.0101)	(0.0004)	(0.0101)
Observations	44,170,732	44,170,732	44,170,732
Dependent Variable Mean	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 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: Heterogeneity — Non-Firearms vs Firearms

	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
	(0.0094)	(0.0007)
Observations	43,779,771	43,779,771
Dependent Variable Mean	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 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: Heterogeneity — Location of the Crime

	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
Dependent Variable Mean	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 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: Heterogeneity — Time of the Day

	Intimate Partner Violence per 100,000 people			
	Morning	Afternoon	Evening	Night
	(1)	(2)	(3)	(4)
Temperature (°C)	6.57e-05**	9.30e-05**	0.0002**	0.0001**
	(3.20e-05)	(4.57e-05)	(9.13-05)	(7.20e-05)
Precipitation (m)	-0.0020	4.68e-05	-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
Dependent Variable Mean	0.00907	0.01353	0.02075	0.01332
Jurisdiction-Month-Year FE	✓	✓	✓	✓
Week-of-Year FE	✓	✓	✓	✓
Day-of-Week FE	✓	✓	✓	✓
Jurisdiction-Location Population Weights	✓	✓	✓	✓

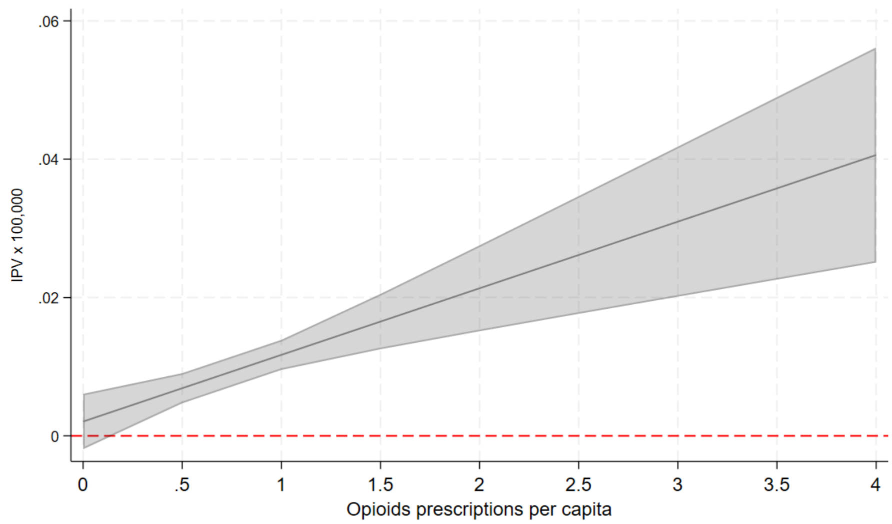
Notes: The dependent variable is the number of intimate partner violence per 100,000 people. Temperature is the daily average temperature measured in degrees Celsius (°C). Precipitation is the total daily precipitation measured in metres (m). Standard errors are clustered at the county level. Significance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

Table A15: Heterogeneity — Substance Use

	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)	(1.12e-07)	(1.50e-07)	(1.29e-06)	(9.35e-07)	(2.19e-06)
Precipitation (m)	-0.0010	-4.32e-06	0.0001	4.26e-05	-0.0003	-7.7e-05
	(0.0038)	(6.45e-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
Dependent Variable Mean	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 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: Temperature and Opioid prescription reformulation



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: Heterogeneity — County-level Socio-demographics

	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
Dependent Variable Mean	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 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.

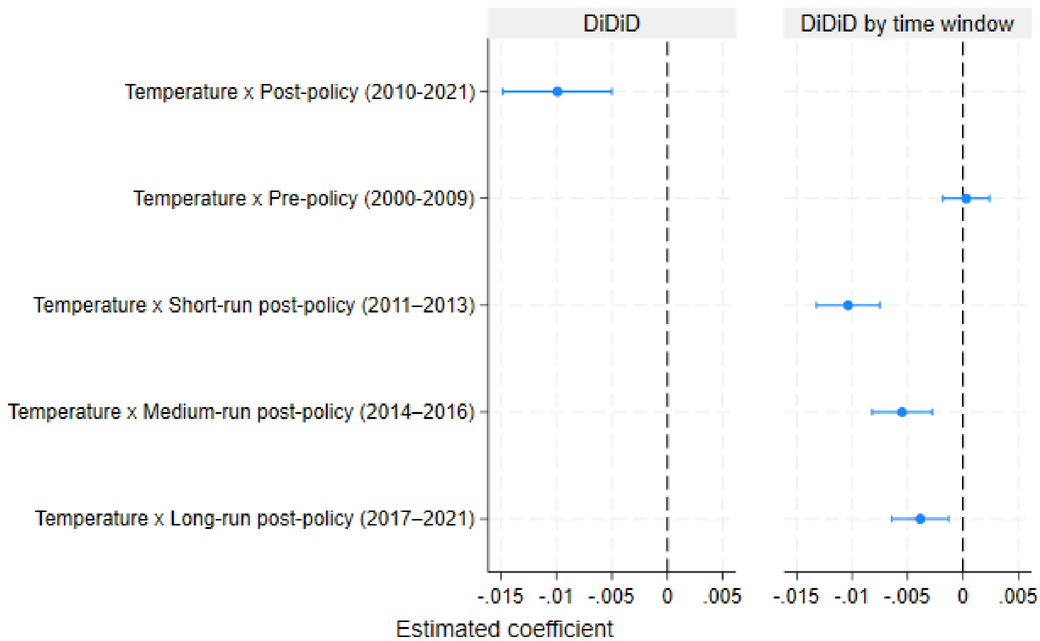
Table A17: Heterogeneity — Climatic Conditions

	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
Dependent Variable Mean	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 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.

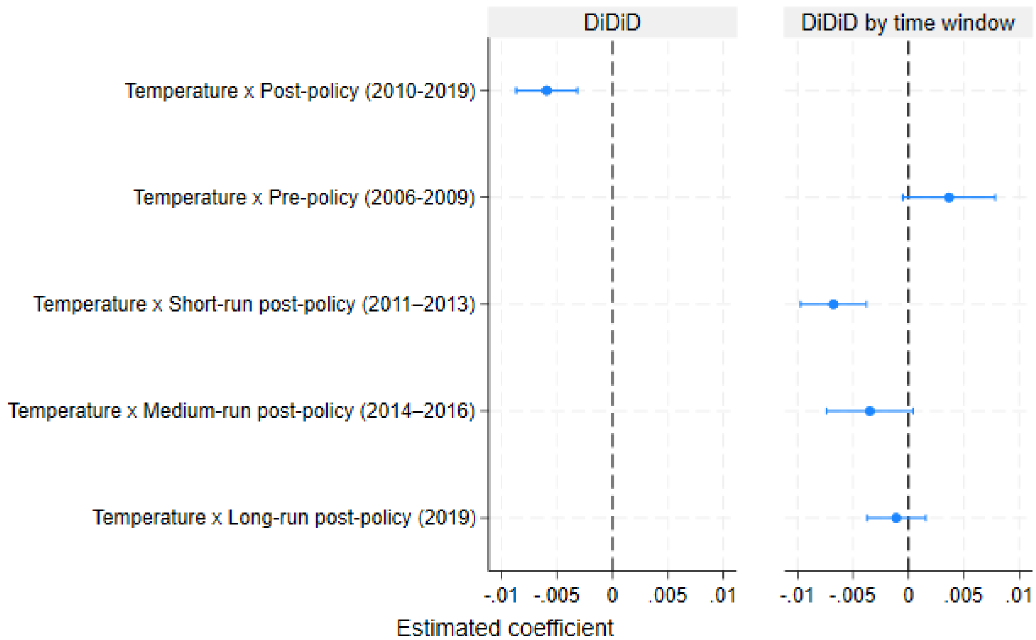
A.2.3 Opioid reformulation

Figure A5: Triple difference (DiDiD) of Opiod reformulation policy on the temperature-IPV relationship with alternative fixed effects



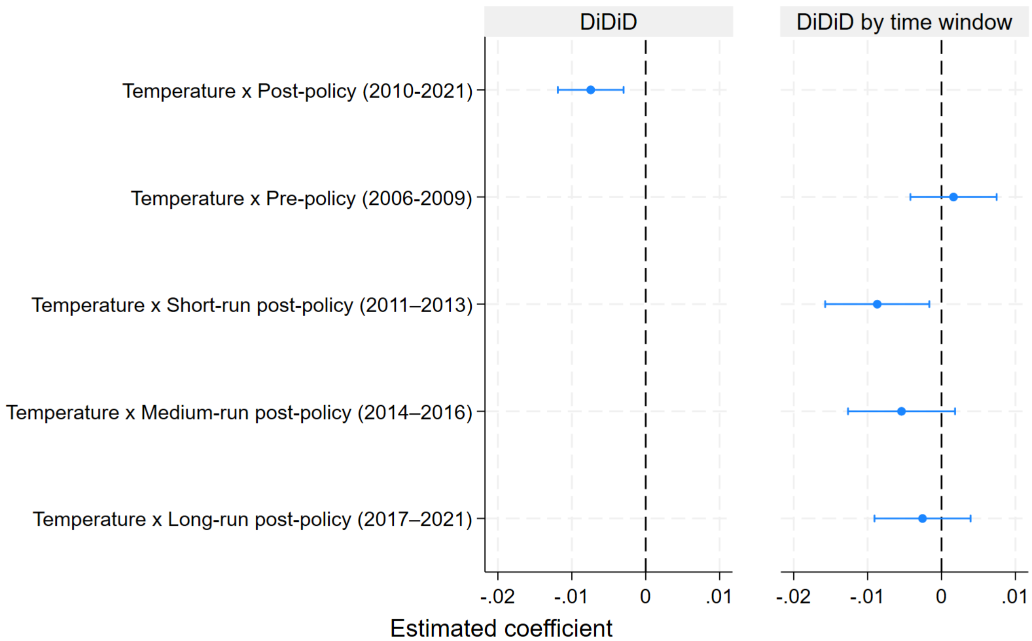
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opiod prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation years, 2010-2021, 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 jurisdiction-day, jurisdiction-month-year, and date fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the county-level.

Figure A6: Triple difference (DiDiD) of Opiod reformulation policy in 2010 on the temperature-IPV relationship (excluding Covid-19 period)



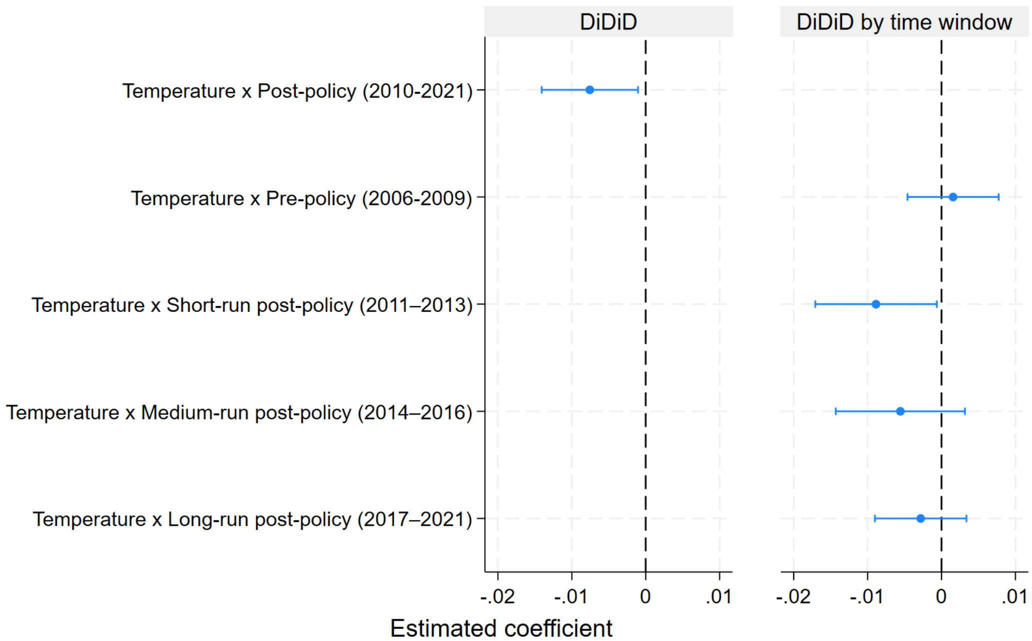
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opiod prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation years, 2010-2019, and in the right graph an indicator variable (short-run) equal to one for the years immediately following reformulation, 2011 to 2013, another one (medium-run) equal to one for the years 2014 to 2016, and another indicator variable (long-run) for the years 2017-2019, several years post-reformulation. We exclude observations in the Covid-19 period defined as years 2020 and 2021. 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.

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



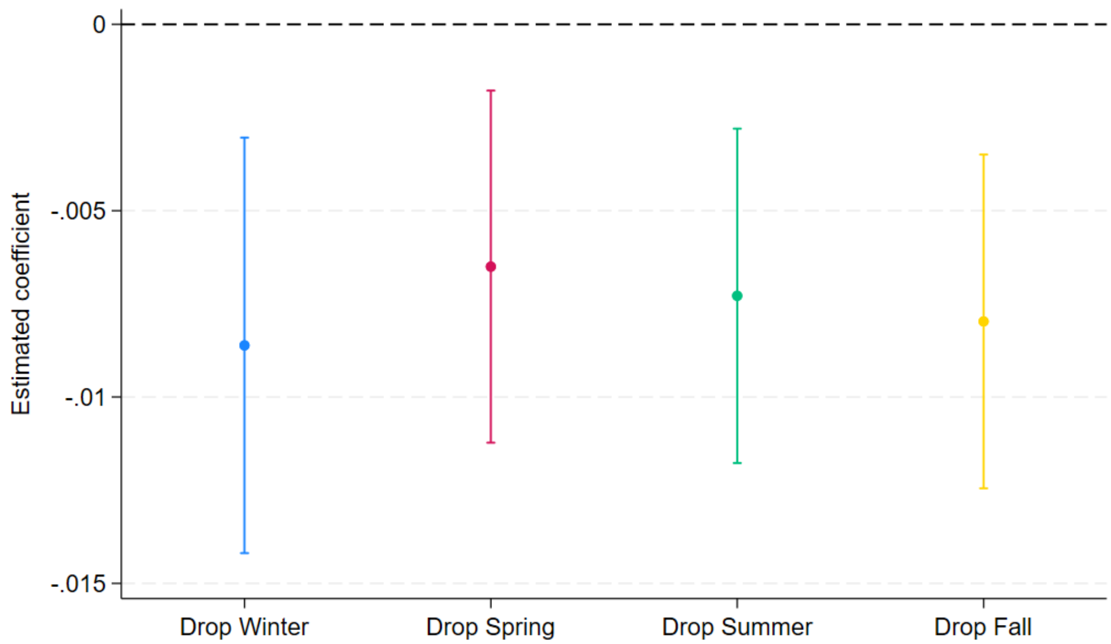
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opiod prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation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

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



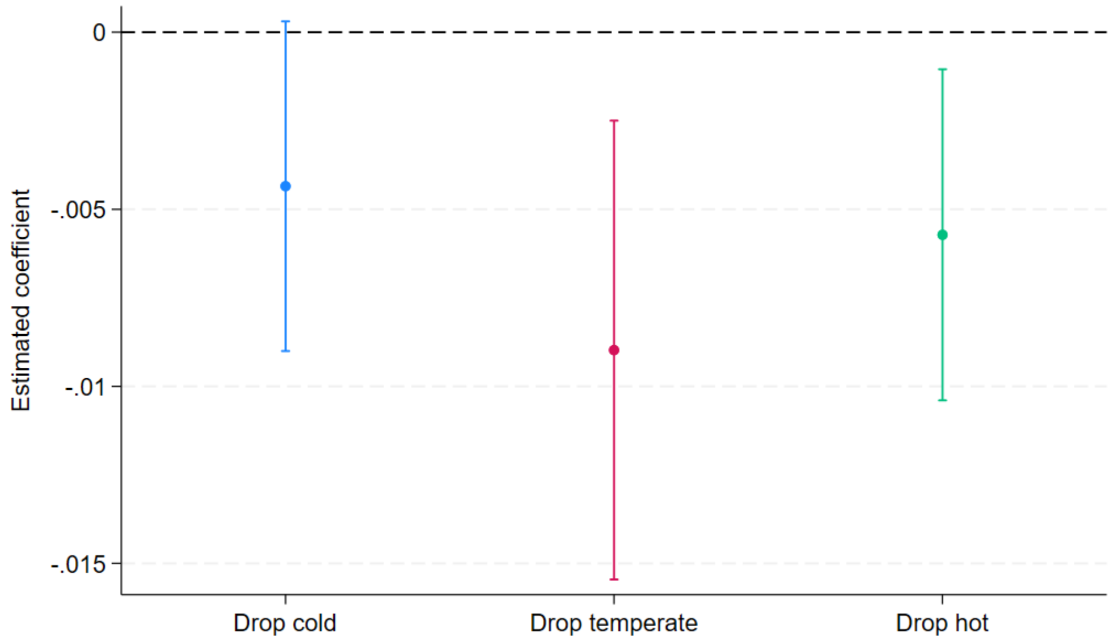
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, pre-intervention exposure as the population-weighted mean per capita opiod prescription, and in the left graph an indicator variable that takes the value of one for the post-reformulation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



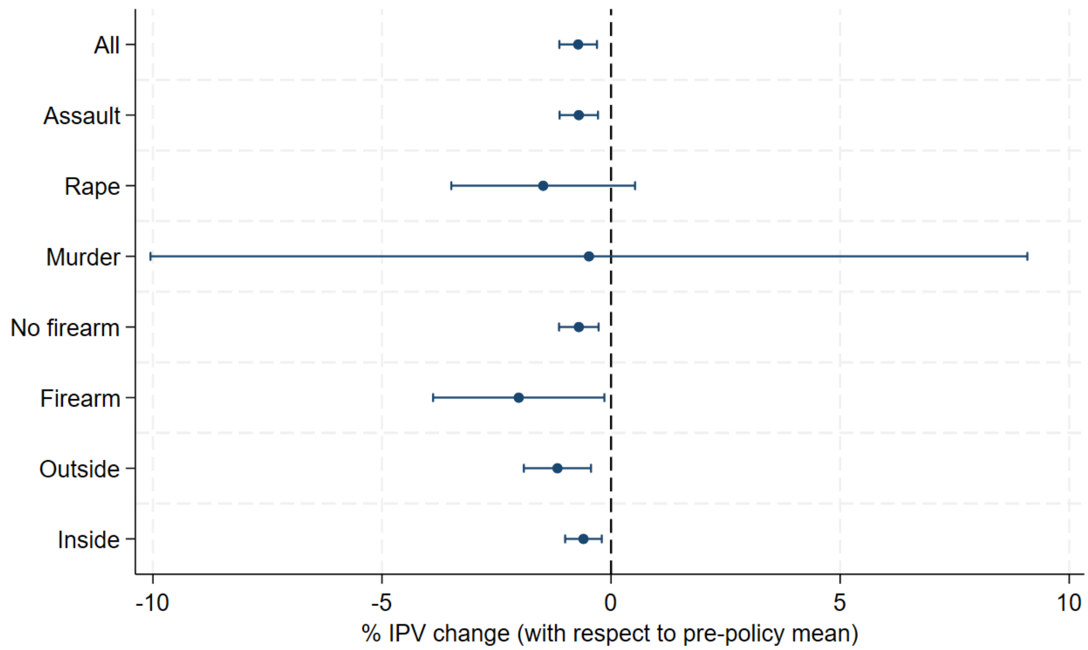
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, a dummy post-2010, and pre-intervention exposure as the population-weighted mean per capita opiod prescription in a regression where we restrict the estimation sample leaving one 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. The coefficient on the restricted sample excluding cold counties is statistically significant at 90% level.

Figure A11: Effect of the Opiod reformulation on the temperature-IPV relationship by type of offense



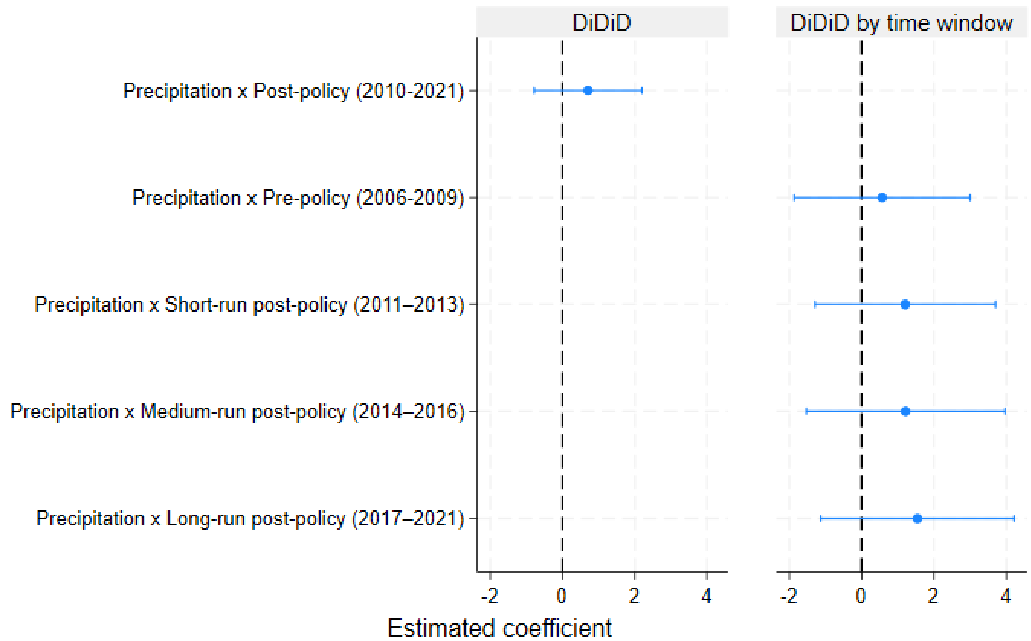
Notes: The figure plots the coefficients from the triple interaction term between average daily county-level temperature, a dummy post-2010, and pre-intervention exposure as the population-weighted mean per capita opiod prescription scaled by the pre-policy IPV average (before 2010). The regression controls for precipitation, year-specific temperature, 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 A18: The Relationship between Temperature and Intimate Partner Violence

	Intimate Partner Violence per 100,000 people		
	(1)	(2)	(3)
Panel A: DiDiD			
Nighttime temperature × Opioid exposure	0.00980***	0.00957***	0.00936***
	(0.00236)	(0.00233)	(0.00232)
Nighttime temperature × Opioid exposure × Post-policy	-0.00819***	-0.00793***	-0.00771***
	(0.00226)	(0.00222)	(0.00221)
Panel B: DiDiD by time window			
Nighttime temperature × Opioid exposure	0.00751**	0.00791**	0.00792**
	(0.00347)	(0.00346)	(0.00345)
Nighttime temperature × Opioid exposure × Pre-policy	0.00228	0.00166	0.00144
	(0.00287)	(0.00281)	(0.00276)
Nighttime temperature × Opioid exposure × Short-run post-policy	-0.00905**	-0.00938***	-0.00931***
	(0.00361)	(0.00358)	(0.00356)
Nighttime temperature × Opioid exposure × Medium-run post-policy	-0.00552	-0.00584	-0.00577
	(0.00362)	(0.00359)	(0.00356)
Nighttime temperature × Opioid exposure × Long-run post-policy	-0.00238	-0.00283	-0.00296
	(0.00324)	(0.00325)	(0.00327)
Nighttime	6pm-6am	8pm-6am	8pm-8am
Observations	8,494,904	8,494,904	8,494,904
Dependent Variable Mean	0.095	0.095	0.095
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 per 100,000 people. Nighttime temperature is the average hourly temperature in the period of the day report in the row "Nighttime" for each column, 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 A12: Effect of the Opiod reformulation 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.