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Access to guns in the heat of the moment: More restrictive gun laws mitigate the effect of temperature on violence

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Abstract
Gun violence is a major problem in the United States, and extensive prior work has shown that higher temperatures increase violent behavior. We consider whether restricting the concealed carry of firearms mitigates or exacerbates the effect of temperature on violence. We use two identification strategies that exploit daily variation in temperature and variation in gun control policies between and within states. We provide evidence that more prohibitive concealed-carry laws attenuate the temperature–homicide relationship. Our findings are consistent with more-prohibitive policy regimes reducing the lethality of altercations.

Key words: right-to-carry, temperature, crime, homicide
JEL Classification: K42; Q51; I18

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1 Introduction

Gun violence imposes significant costs on society. Loss of life is by far the largest of these costs. This is a particular problem in the United States, where gun violence is the leading cause of death for Black Americans aged 15-24 (CDC, 2020). Given the well-established link between higher temperatures and violent behavior, this problem is likely to worsen as temperatures rise due to climate change, unless this link can be mitigated.

In this paper, we consider whether gun regulations, particularly those governing the concealed carry of handguns, can mitigate the effect of temperature on homicide rates. We leverage the causal relationship established in the environmental economics, physiology, and psychology literatures, which shows that higher temperatures act as an exogenous shock that increases violent behavior.[1] Combining jurisdiction-day variation in temperature with state-by-month variation in concealed-carry laws, we then test whether the effect of temperature on violent behavior varies with different policy regimes. Specifically, we examine whether strict concealed-carry laws mitigate or exacerbate temperature-induced changes in homicide rates, holding other factors constant.

To engage with different identification concerns, we use two different research designs. First, we exploit between-state differences in the policy regime, using a Differences-in-Temperature (DiT) research design. The intuition for this approach is closest to a difference-in-differences research design, with temperature playing the role of time. The DiT design exploits differences in the temperature–homicide relationship between states with different concealed-carry laws. By considering average effects between places, rather than changes in policy regime over time within a place, this approach avoids concerns that changes in gun laws are confounded by *temporary* changes in local preferences or priorities that soon revert

[1] The existing literature has posited that higher temperatures could affect criminal activity through a number of channels, including: changes in police behavior, as suggested by Heilmann and Kahn (2019); an increase in the likelihood that people go outside, which increases the likelihood of social interaction, the availability of potential victims, and the likelihood that an altercation arises (Jacob, Lefgren and Moretti, 2007); physiological or psychological mechanisms that affect aggressive and impulsive behavior (Anderson, 2001; Groves and Anderson, 2016).

back to normal – as might happen in the aftermath of a mass shooting, when gun violence is particularly salient. However, the design relies on the assumption that there are no other differences between states that also moderate the temperature–homicide relationship.

Second, we exploit panel variation in policy changes using a Difference-in-Differences-in-Temperature (DiDiT) research design. The intuition for this approach is closest to a triple-difference research design. The triple interaction of temperature, state, and "post", identifies the moderating effect of concealed-carry laws under the assumption that the temperature–homicide relationship would have remained the same absent the law change. The DiDiT approach is not affected by differences between states that might moderate the temperature–homicide relationship. However, the DiDiT approach could be biased if any other changes that coincide with the policy change also moderate the temperature–homicide relationship.

Both approaches yield similar results. Using daily data from the National Incident-Based Reporting System (NIBRS) from 1991-2016, we find that gun laws that limit residents' ability to carry concealed firearms mitigate the effect of temperature on homicides. Using our DiT approach, we estimate that a 1°C increase in the daily average temperature is associated with 0.000511 fewer daily homicides per 100,000 people during more-prohibitive policy regimes — a 4.2% decrease compared to the mean. Using our DiDiT approach, we estimate that a 1°C increase in the daily average temperature is associated with 0.000349 fewer daily homicides per 100,000 people during more-prohibitive policy regimes — a 2.9% decrease compared to the mean.

In additional analysis, we document that our estimates are driven by homicides involving guns, as one would expect if we are isolating the differential effect of gun laws. We do not estimate any increase in the effects on non-gun homicides. We also present findings that more-prohibitive gun laws are not associated with any differential effect of temperature on aggravated assaults. These findings are consistent with more-prohibitive policy regimes reducing the lethality of altercations.

We also provide new insights into the mechanisms underlying the temperature–homicide relationship. While there are fewer homicides on days with more precipitation, we do not estimate any differential effect of concealed-carry laws on the precipitation–homicide relationship. This finding suggests that the physiological and psychological effects of heat may be more important in explaining the temperature–homicide relationship than increased social interaction. Further support for this interpretation comes from estimates that examine when and where homicides occur. We estimate larger differential effects on homicides in the afternoon and evening hours, when temperatures are highest. We also estimate that higher temperatures are associated with more homicides both within the home and outside.[2]

Our findings contribute to the lengthy and contentious literature in economics, criminology, and public health, studying the effect of gun laws on violent crime.[3] Instead of evaluating the direct effect of gun laws on violent crime we explore how gun laws interact with local shocks to mitigate or exacerbate the effects of those events. We are aware of only one other paper that considers how gun laws interact with local events. In concurrent work, Koenig and Schindler (2021) test for differential effects of a spike in handgun purchases on homicides, comparing outcomes in places with firearm purchase delay laws to those without such laws. They find that purchase delay laws reduced the effect of the Sandy Hook shooting on subsequent gun purchases and homicides by 7-8% and 2%, respectively. Like Koenig and Schindler (2021), we find economically meaningful effects, with more-prohibitive gun laws substantially mitigating the effect of temperature on homicides. In both contexts, the marginal homicide is likely impulsive rather than premeditated. This is important to

[2]Evidence of a temperature–homicide relationship within the home is consistent with other studies that document higher temperature affecting decision-making even in climate-controlled environments. Hayes and Saberian (2019) document that higher outdoor temperatures reduce the likelihood of favorable judge decisions in immigration cases, despite those decisions being made in climate controlled conditions.

[3]The existing literature finds mixed evidence, and estimates tend to be sensitive to choice of empirical specification. Lott and Mustard (1997) and Moody (2001) find that RTC laws are associated with reduced violent crime. Ludwig (1998) finds that such laws are associated with increases in adult homicide rates. Black and Nagin (1998) and Ayres and Donohue (2003) find no association between RTC laws and violent crime. Manski and Pepper (2018) demonstrate that results can be sensitive to bounding exercises and find suggestive evidence that the association between RTC laws and crime changes over time, estimating reductions in the 1990s but increases in the 2000s. Using data from 1977 through 2014, Donohue, Aneja and Weber (2019) find that RTC laws are associated with increases in violent crime. See Wellford, Pepper and Petrie (2005) and Smart et al. (2023) for a more comprehensive review.

understand because crimes of passion may be less influenced by other policy levers, such as the probability of getting caught or potential punishments.

More generally, our findings and those of Koenig and Schindler (2021) suggest that *all* evaluations of gun laws will be sensitive to external factors. To the extent that temperature-driven homicides and other impulsive homicides account for a large share of all homicides, we may expect there to be greater heterogeneity in the overall effects of laws, regulations, and policies over time and space. In hotter years, temperature will contribute more, while in cooler years, it will contribute less. In a political context where it is difficult to strengthen gun laws, our findings highlight the need to better understand the extent to which we can influence the external factors that shape violent behavior.

We also contribute to an established literature documenting the effects of temperature on violent behavior (Hsiang, Burke and Miguel, 2013; Ranson, 2014; Dell, Jones and Olken, 2014; Burke, Hsiang and Miguel, 2015; Carleton and Hsiang, 2016) and a growing literature highlighting how the economic and policy environment shapes the translation of environmental conditions into economic and social damages (Mullins and White, 2019; Colmer, 2021; Colmer et al., 2021; Garg, McCord and Monftfort, 2023). Compared to the existing literature we use more detailed daily data on crime to estimate the temperature–homicide relationship and provide the first evidence that gun laws affect the temperature–homicide relationship. We also provide evidence that the dominant mechanism driving the temperature–homicide relationship is physiological rather than social, at least in the context of the United States.[4]

The paper proceeds as follows: section 2 describes our data; section 3 describes our two empirical strategies; section 4 presents our main results; section 5 presents additional results

[4]Existing evidence has tended to come from field or laboratory experiments, or in contexts where the behavioral mechanism is isolated. Higher temperatures have been shown to: increase horn honking when cars fail to pull away at green lights (Kenrick and MacFarlane, 1986); increase tension, aggression, and negative perceptions of offenders during police fire arms training (Vrij, Van Der Steen and Koppelaar, 1994); increase the likelihood that pitchers hit batters during baseball games when batters "crowd the plate", or if a teammate has been hit in a previous inning (Reifman, Larrick and Fein, 1991; Larrick et al., 2011); and increase the likelihood of aggressive penalties in NFL football games (Curtis et al., 2016). More recently, Mukherjee and Sanders (2021) show that higher temperatures cause more violent incidents in prisons without air conditioning, a context where restrictions on inmates' movements help isolate physiological responses to temperature from any effects driven through increased social interactions.

exploring mechanisms and heterogeneity; section 6 discusses the implications of our results.

2 Data

2.1 Homicide

Our main outcome measure is the number of nonnegligent homicides reported to police, per 100,000 residents. Our findings are robust to alternative transformations of this outcome variable, including whether any homicides occurred within a jurisdiction on a given day. We focus on homicides because this crime type is the most consistently reported across jurisdictions and over time and is less subject to measurement error.[5]

2.1.1 NIBRS

Our main data source is the FBI's National Incident-Based Reporting System (NIBRS).[6] The NIBRS data includes more detailed information than the FBI's Uniform Crime Reports (UCR), including information on the hour and date of the offense, where the offense took place (e.g. at home or on the street), and whether any weapons were involved. Incidents are associated with a specific police department (ORI, which we will also refer to as jurisdiction). However, fewer departments report to NIBRS than to the FBI's Uniform Crime Reports (UCR). Figure **??** shows a map of jurisdictions in our NIBRS sample. NIBRS tends not to include large cities, and places in the northeast and west are underrepresented.

We use NIBRS data from 1991 through 2016. We gather data on homicides and aggregate these data to the jurisdiction-day level. This allows us to match them to daily average

[5]Most studies focus on homicide as the primary outcome of interest for the same reason we do: there is less measurement error in reporting for this type of crime. While other types of crimes may go unreported to the police, the vast majority of homicides are reported. Two exceptions are studies using gunshot sensor data on shootings: Carr and Doleac (2016), and Carr and Doleac (2018). These data provide useful complements to homicide data since shootings occur much more often, and the sensors reduce concerns about nonrandom reporting. However, data are available only in a limited number of cities and in recent years.

[6]In additional analyses we also use the FBI's Uniform Crime Reports (UCR). However, the data is available only at the monthly level. This is less than ideal for our study because we want to match crimes with local temperatures, which fluctuate on a daily basis.

temperatures. This results in an unbalanced panel, as departments drop in and out of the sample over time; we discuss how we account for the changing composition of the panel in the sample restrictions section below.

2.1.2 Sample Restrictions

The primary challenge associated with using NIBRS data is that the number of reporting agencies varies over time. To account for this, we construct panels that are balanced at the year level and exploit within-year variation to identify our estimates.

To do this, we drop observations for any reporting agency that did not report 12 months of data for that year. This includes agencies that only report on a quarterly, biannual, or annual basis, since we cannot be sure how crimes were allocated across the months. Since zeros are often recorded for all types of crime when an agency did not report its data to the FBI, we consider any month during which an agency reported zero total crimes to be a missing observation. After eliminating years during which there were any missing monthly observations, we then sum the total number of reported crimes from remaining agencies to produce a total for each jurisdiction-day.

Our final analysis dataset includes 5,934 jurisdictions from 1991–2016, providing 13,495,334 unique jurisdiction-day observations. Table 1 presents summary statistics.

2.2 Weather Data

Data on weather, updated from Schlenker and Roberts (2009), come from the PRISM Climate Group. These data provide daily minimum and maximum temperature, as well as total precipitation on a 2.5 $\times$ 2.5 mile grid for the contiguous United States between 1950 and 2017. Using these data, we calculate the daily average temperature and total precipitation for each county-by-day observation. We then match counties to jurisdictions; counties typically encompass multiple jurisdictions.

2.3 Policy Data

We code concealed-carry laws at the state-month level, considering a place treated by a particular policy if it was in effect in that state for the majority of a given month.[7] These state-level laws determine whether a permit is required to carry a concealed firearm on their person, and specify who is eligible to obtain a permit. In some states, the legal ability to carry a concealed firearm is completely unrestricted; "shall issue" policies are slightly more restrictive but instruct government officials to provide permits to all eligible residents; "may issue" policies provide more discretion to local officials to decide who can receive a permit and thus are considered substantially more restrictive in practice; finally, a state might prohibit any resident from carrying a concealed firearm in public. More lenient laws are often referred to as Right-to-Carry (RTC) laws. We code concealed-carry gun laws into four categories: unrestricted, shall-issue, may-issue, and prohibited. To improve statistical power, we aggregate the first two types of laws into a "less prohibitive" category, with the third and fourth types making up a "more prohibitive" category. In robustness tests, we also use state-month variation on whether background checks and waiting periods — two other commonly analysed types of gun law — were in place. In Figure 1 we see that there has been a gradual movement from more-prohibitive laws to less-prohibitive laws over the period of interest.

3 Empirical Strategy

Based on existing literature, we expect that confrontations are more likely to occur and escalate when it is warmer outside, providing within-place variation in violent behavior that is unrelated to local gun laws. Table 2 and the additional results presented in Appendix A provide evidence of this baseline relationship in our sample. We argue that the outcome or lethality of any confrontation may depend on whether or not guns are available, which

[7] We are grateful to Christopher Poliquin, Michael Luca, and Deepak Malhotra for sharing this data with us.

may, in turn, depend on local gun laws. We exploit this exogenous variation in the supply of violence to understand the extent to which concealed-carry laws mitigate or exacerbate the number of homicides committed.

To do this, we use two research designs, which we refer to as "Differences-in-Temperature" (DiT) and "Difference-in-Differences-in-Temperature" (DiDiT) designs. Both research designs require that daily temperature realizations are uncorrelated with other factors that also affect the likelihood of committing a violent crime. By exploiting exogenous daily fluctuations in temperature, we believe this assumption is plausible.

3.1 Differences-in-Temperature

One threat to identification is that concealed-carry law changes may coincide with other temporary changes in preferences or local priorities. For example, a local crime event, such as a mass shooting, might make gun violence temporarily more salient, leading to a change in concealed-carry laws, as well as demand for guns and attitudes toward gun users. In such contexts, estimates based on policy changes could be confounded by these other changes.

To address this identification concern, we use a Differences-in-Temperature (DiT) strategy. The DiT design compares the effect of daily temperature fluctuations on homicides between places with different concealed-carry laws. The policy variation we exploit is cross-sectional, which is not a problem if the primary threat to identification is that changes in gun laws are confounded by temporary changes in public sentiment or local priorities in the months around the policy change. This identification strategy relies on the assumption that no other time-invariant differences exist between policy regimes that could also moderate the temperature–homicide relationship.

We estimate the following empirical specification,

$$\begin{aligned} y_{j,d} &= \alpha_{m(d)} + \gamma_{m(d)} f(w_{j,d}) + \delta_{m(d)} \text{More-Prohibitive}_{s(j),m(d)} \qquad (1) \\ &\quad + \beta_1^w f(w_{j,d})_{j,d} \times \text{More-Prohibitive}_{s(j),m(d)} + \varepsilon_{j,d}, \end{aligned}$$

where $y_{j,d}$ denotes an outcome observed for jurisdiction j and day d, and $f(w_{j,d})$ denotes a function of weather variables that includes daily average temperature, temperature$_{j,d}$, and total daily precipitation, precipitation$_{j,d}$. We control for precipitation to account for the correlation between temperature and precipitation. More-Prohibitive$_{s(j),m(d)} \in \{0,1\}$ indicates state-month-year observations where more-prohibitive concealed-carry laws are in place, where subscript $s(j)$ denotes the state of jurisdiction j and subscript $m(d)$ denotes the month-year of day d.[8] We include month-year fixed effects and interact these fixed effects with temperature$_{j,d}$, precipitation$_{j,d}$, and More-Prohibitive$_{s(j),m(d)}$, controlling for time-varying changes in the direct effects of temperature, precipitation, and concealed-carry laws on our outcomes of interest.[9]

Our variable of interest is temperature$_{j,d}\times$More-Prohibitive$_{s(j),m(d)}$. The intuition for this approach is closest to a difference-in-differences research design, with temperature playing the role of time. In a cross-sectional setting with only one month of data, β_1^{temp} would capture the differential temperature–homicide relationship between states with more- and less-prohibitive gun laws in month m. Given that we have data for many months, in our context β_1^{temp} captures a variance-weighted average of the cross-sectional difference between periods.

Interpreting the interaction term as a causal moderator requires the assumption that no other (unobserved) policies or time-invariant local factors, which are correlated with these laws, also moderate the temperature–homicide relationship. Unlike much of the existing literature on gun laws, our emphasis on the effect of temperature elevates the omitted variable bias concern to the level of the interaction term. Although there are likely many differences between states that could directly influence violent crime, it is plausible that many of these factors do not affect the temperature–crime relationship. Nevertheless, we cannot rule out

[8]We define more-prohibitive laws to be in effect when the ability to carry a concealed gun is prohibited or subject to a may-issue permit policy. For each month, the policy that was in place for the greatest number of days is applied.

[9]We also include week of year and day of week fixed effects to control for the extent to which seasonality in the weather and homicides are correlated. Our findings are not sensitive to these additional controls.

the possibility that a subset of the differences influencing violent crime might also affect the temperature–crime relationship.

3.2 Difference-in-Differences-in-Temperature

As noted, the residual threat to identification when using the Difference-in-Temperature approach is that places with different concealed-carry policies are different in other ways, and that these other differences also affect the temperature–homicide relationship.

If these unobservable confounders are fixed over time, we can address this threat by using law changes in a panel design. We refer to this approach as the Difference-in-Differences-in-Temperature (DiDiT) approach, which exploits within-place changes in concealed-carry laws alongside within-place variation in temperature over time.

We estimate the following empirical specification,

$$\begin{aligned} y_{j,d} \quad &= \quad \alpha_{s(j),m(d)} + \gamma_{m(d)} f(w_{j,d}) + \gamma_{s(j)} f(w_{j,d}) \\ &\quad + \beta_2^w f(w_{j,d}) \times \text{More-Prohibitive}_{s(j),m(d)} + \varepsilon_{j,d}, \end{aligned} \tag{2}$$

The intuition for this approach is closest to a triple differences research design. The three dimensions of the triple-difference are state, month-year, and temperature. In the above specification, we control for state-month-year fixed effects. We also include month-year and state-specific temperature and precipitation controls, accounting for time-varying changes and state-specific differences in the direct effects of temperature and precipitation on homicide.

The triple interaction of temperature, state, and "post" identifies β_2^{temp} under the assumption that the temperature–homicide relationship would have remained the same absent the change of law. Under this assumption, β_2^{temp} tells us the degree to which the temperature–homicide relationship changes when a more-prohibitive concealed-carry law is in place.[10]

[10] Given the staggered timing of treatment, this design is subject to the negative weighting concerns raised by the recent difference-in-differences literature (de Chaisemartin and D'Haultfœ uille, 2020; Goodman-

We also implement a more restrictive version of the DiDiT design in which we control for jurisdiction-state-month-year fixed effects,

$$
\begin{aligned}
y_{j,d} \quad = \quad & \alpha_{j,m(d)} + \gamma_{m(d)} f(w_{j,d}) + \gamma_j f(w_{j,d}) \\
& + \beta_3^w f(w_{j,d}) \times \text{More-Prohibitive}_{s(j),m(d)} + \varepsilon_{j,d},
\end{aligned}
\tag{3}
$$

By exploiting within-jurisdiction variation in daily temperature and precipitation, this more restrictive specification provides even more support for the assumption that day-to-day temperature and precipitation realizations are uncorrelated with other factors that also affect the likelihood of committing a violent crime.

Standard Errors In both research designs, we cluster standard errors at the state level, as this is the geographic level at which the policy varies. Our results are also robust to the use of Conley standard errors that account for more arbitrary patterns of spatial dependence. Statistical inference was most conservative when clustering at the state level.

3.3 The Baseline Temperature–Homicide Relationship

Both the DiT and DiDiT research designs include month or location-month specific temperature slopes, allowing the temperature–homicide relationship to vary flexibly over time and space. However, this means that only the relative effect of temperature between policy regimes is identified. To provide readers with a benchmark understanding of the temperature–homicide relationship in our setting, we also present estimates of the daily temperature–homicide relationship.

We start by reporting the unconditional relationship between temperature and homicide, documenting the empirical relevance of the association in the raw data,

Bacon, 2021; Callaway and Sant'Anna, 2021). We will show that our estimates are robust to accounting for staggered timing.

$$y_{j,d} = \alpha + \gamma f(w_{j,d}) + \varepsilon_{j,d} \tag{4}$$

We then estimate the average temperature–homicide relationship, using empirical specifications that align most closely with our DiT and DiDiT specifications. To provide a benchmark temperature–homicide relationship for our DiT analysis, we estimate the following specification,

$$y_{j,d} = \alpha_{m(d)} + \gamma f(w_{j,d}) + \varepsilon_{j,d} \tag{5}$$

This specification controls for month-year fixed effects, controlling for other factors that are common across jurisdictions that correlate with month-to-month variation in the daily temperature–homicide relationship.

To provide a benchmark temperature–homicide relationship for our DiDiT analysis, we estimate the following specification,

$$y_{j,d} = \alpha_{\ell,m(d)} + \gamma f(w_{j,d}) + \varepsilon_{j,d} \tag{6}$$

where $\alpha_{m(d),\ell}$ represents state-month-year or jurisdiction-state-month-year fixed effects, controlling for state- or jurisdiction-specific time-varying factors that correlate with month-to-month variation in the daily temperature–homicide relationship. In our analysis of the baseline temperature–homicide relationship, we cluster standard errors at the county level — the level of spatial variation in the temperature and precipitation data. Our results are also robust to clustering at the state level or to using Conley standard errors that account for more arbitrary patterns of spatial dependence.

4 Results

In this section, we present the results of our analysis. First, we present evidence on the baseline temperature–homicide relationship. These results provide context and a benchmark to compare our DiT and DiDiT estimates.

4.1 The Baseline Temperature–Homicide Relationship

We begin by presenting evidence on the baseline temperature–homicide relationship. The results of this analysis are presented in Table 2. In column (1) we present the unconditional relationship between daily temperature variation and the number of homicides per capita. We estimate that, on average, a one-degree Celsius increase in daily average temperature is associated with 0.000213 more homicides per 100,000 people, a 1.7% increase compared to the mean. We do not estimate a significant unconditional relationship between precipitation and the number of homicides per 100,000 people.

In column (2), we present an estimate of the within-month temperature–homicide relationship, using the specification in Equation 5. We estimate that, on average, a one-degree Celsius increase in daily average temperature is associated with 0.000688 more homicides per 100,000 people, a 5.7% increase compared to the mean — a more responsive relationship than the unconditional association. Unlike the unconditional relationship, we estimate that a one millimeter increase in daily precipitation is associated with 0.0000609 fewer homicides per 100,000 people, a 0.5% decrease compared to the mean. This finding is consistent with the premise that there are fewer homicides on rainy days because there is less social interaction. These estimates provide a benchmark temperature–homicide relationship for our DiT analysis.

In column (3), we exploit within-state-month variation in daily temperature. We estimate that, on average, a one-degree Celsius increase in daily average temperature is associated with 0.000170 more homicides per 100,000 people, a 1.4% increase compared to the mean. This estimate is smaller than the within-month relationship, as it controls for both time-invariant and time-varying differences between states in the temperature–homicide relationship. We also estimate a smaller baseline relationship between precipitation and the number of homicides per 100,000 people using this specification (-0.0000506/mm), a 0.4% decrease compared to the mean. These estimates provide a benchmark temperature–homicide relationship for our state-level DiDiT analysis.

In column (4), we exploit within-jurisdiction-month variation in daily temperature. We estimate that, on average, a one-degree Celsius increase in daily average temperature is associated with 0.000105 more homicides per 100,000 people, a 0.8% increase compared to the mean. By absorbing both time-invariant and time-varying differences between jurisdictions, we are left with less residual variation in the temperature–homicide relationship. The precipitation-homicide relationship, by contrast, is similar in magnitude (-0.0000497/mm). These estimates provide a benchmark temperature–homicide relationship for our jurisdiction-level DiDiT analysis.

In Panels B and C of Table 2, we split the data between "More-Prohibitive" and "Less-Prohibitive" policy regimes. In all specifications, we estimate that, on average, the relationship is less responsive during "More-Prohibitive" policy regimes. Figure 2 presents a visual comparison of the temperature–homicide relationship using the most restrictive within-jurisdiction-month variation. We estimate a positive temperature–homicide relationship in less-prohibitive policy regimes and a flat relationship in more-prohibitive policy regimes. This exercise is descriptive. To consider the causal effect of RTC laws on the temperature–homicide relationship we turn to our DiT and DiDiT research designs.

Appendix A presents additional results, exploring sensitivity in the baseline temperature–homicide relationship to alternative nonlinear specifications (Figures A1 and A2) and alternative measures of temperature (Table A1). We also explore how the relationship varies between different climates and seasons (Tables A2 and A3). Overall, we estimate that the relationship is quite linear, consistent with previous work, and not particularly sensitive to restrictions on climate, seasons, or alternative measurements of temperature.

4.2 Main Results

Table 3 presents the main results from our two research designs. Column (1) presents the estimate from our DiT research design presented in Equation 1. We estimate that a one-degree Celsius increase in temperature is associated with 0.000511 fewer homicides per 100,000 people during more-prohibitive policy regimes, a 4.2% reduction compared to the mean. Compared to our baseline estimate of the temperature–homicide relationship using month-year fixed effects (0.000641/1°C), our DiT estimate suggests that more-prohibitive concealed-carry laws substantially attenuate the temperature–homicide relationship.

Column (2) imposes a sample restriction, dropping observations for one year on either side of any policy changes. This "donut specification" gives us a sample that is more plausibly free of (temporary) confounding changes in local preferences or priorities, meaning that our comparisons between states are more likely to reflect a stable policy environment. The estimated coefficient is very similar in magnitude to the estimates in column (1).

Column (3) presents the state version of our DiDiT approach presented in Equation 2. Under the assumption that the temperature–homicide relationship would have remained the same absent the law change, the coefficient estimate captures the effect of more-prohibitive concealed-carry laws on the temperature–homicide relationship. We estimate that a one-degree Celsius increase in temperature is associated with 0.000332 fewer homicides per 100,000 people during more-prohibitive policy regimes, a 2.8% reduction compared to the mean. When compared to the average temperature–homicide relationship presented in column (3) of Table 2, this estimate again suggests that more-prohibitive concealed-carry laws substantially attenuate the temperature–homicide relationship.

Column (4) presents the more restrictive jurisdiction specification presented in Equation 3. This approach includes jurisdiction-month-year fixed effects, month-year specific temperature and precipitation effects, and jurisdiction-specific temperature and precipitation effects. This more restrictive specification means that we are exploiting within-jurisdiction variation in daily temperature, absorbing any residual time-invariant confounding variation between jurisdictions that could be biasing the direct temperature–homicide relationship. The estimated coefficient is very similar in magnitude to the state DiDiT estimate, indicating that such concerns are not of first-order importance. It is also more precisely estimated. Compared to the average temperature–homicide relationship presented in column (4) of Table 2, this estimate provides further evidence that more-prohibitive concealed-carry laws substantially attenuate the temperature–homicide relationship.

In column (5) we engage with concerns about negative weights, which can arise in contexts (like ours) when the introduction of policy changes is staggered (de Chaisemartin and D'Haultfœ uille, 2020; Gardner, 2021; Goodman-Bacon, 2021; Borusyak, Jaravel and Spiess, 2021; Callaway and Sant'Anna, 2021). Given that we are not estimating a standard difference-in-differences model, but rather the differential effect of temperature on homicides following the introduction of less-prohibitive concealed-carry laws, we are not able to implement the new difference-in-differences estimators directly. Instead, we draw inspiration from Callaway and Sant'Anna (2021) and estimate cohort-specific effects, where a cohort is a set of states that changed their policies at the same time. Because we are now comparing a cohort of states that transition to less-prohibitive regimes at the same time with those that never transition, there is no staggered timing. We then produce a sample-weighted average of these cohort-specific effects. Our estimates are slightly smaller but not statistically distinguishable from our other DiDiT estimates, suggesting that concerns about negative weights are not likely to be a first-order concern in this setting.

Figure 3 presents an event study visualization of our results. Specifically, we explore how the temperature–homicide relationship evolves over time, before and after a policy change (from more-prohibitive to less-prohibitive concealed-carry laws, as this is the direction of most policy changes in practice). Before the policy change we see no differential relationship between temperature and homicide — the effect of temperature on homicides is common between more-prohibitive and eventually less-prohibitive states. After the policy change, the responsiveness of the temperature–homicide relationship immediately increases in less prohibitive states compared to more-prohibitive states, resulting in an average relative increase of 0.0003 homicides per 100,000 residents/1°C/day; this change persists for the entire post-period. The rapid and persistent shift from one equilibrium to another is consistent with the policy having caused the observed change, although as with any difference-in-differences style analysis, we cannot rule out the possibility that other concurrent permanent changes in preferences or priorities might also moderate the temperature–homicide relationship.

Our results are robust to a variety of alternative specifications that: use maximum or minimum daily temperature rather than mean temperature (Table B1); restrict the sample to different climates and seasons (Tables B2 and B3); use a binary outcome variable — whether any homicide was reported on a given day (Table B4); aggregate the data to the county-day level (Table B5). We also show that our findings are robust to using UCR data (Table B6).

Finally, we explore the extent to which our findings could be driven by other coinciding gun policies. We use data on background checks (both private sale and dealership checks) and waiting periods (both explicit waiting periods, permit requirements to purchase a gun, and states that were affected by the Brady Act between 1994 and 1998). We focus on waiting periods and background checks because they are consistently measured, commonly evaluated in the existing literature, have been shown to be empirically relevant in affecting violent crime, and because we have data on their implementation at the state-month level for the full sample period. We also use an aggregate index capturing the number of prohibitive gun laws implemented in each state-year during our sample period, provided by `https://www.statefirearmlaws.org` to try capture broader policy variation that is not accounted for by waiting periods and background checks. In the DiT research design, including the interaction between these policy variables and temperature serves to control for other policy differences between states that may also moderate the temperature–homicide relationship and explores the extent to which there is independent variation across different gun policies. In Panel A of Table B7 we estimate that policy regimes with waiting periods and the states with a larger number of prohibitive gun laws are associated with attenuated temperature–homicide relationship when evaluated independently; however, when we control for all of these variables in one regression, only the interaction between *Temperature* × *More-Prohibitive* coefficient remains statistically significant.

In the DiDiT research design, controlling for the interaction of temperature with other gun policies provides an opportunity to consider the likelihood that concurrent changes in preferences or priorities may be empirically relevant as a confounding source of variation. To the extent that changes in gun policies coincide with changes in preferences toward carrying firearms, one might imagine that these changes in preferences might have a constant effect on the temperature–homicide relationship. When estimating the moderating relationship between each policy and the temperature–homicide relationship separately, we only estimate a significant relationship for the *Temperature* × *More-Prohibitive* coefficient (Column 1, Panel B, Table B7). The estimated coefficients for waiting periods, background checks, and the aggregate index are statistically insignificant (Columns 2, 3 and 4, Panel B, Table B7). When we include all interaction terms in one regression, the *Temperature* × *More-Prohibitive* coefficient remains statistically significant and similar in magnitude, indicating that there is independent variation between the different policies and that aggregate changes in gun laws coinciding with right-to-carry laws are unlikely to be driving the results. To the extent that we would expect that changes in gun laws related to waiting periods, background checks, and right-to-carry all coincide with changes in preferences, the absence of an effect for these other policies suggest that our interaction terms are capturing the moderating effect of gun laws. We cannot, however, rule out that our results may be driven by the moderating effect of other laws or policies on temperature that we have not been able to directly control for.

5 Exploring Mechanisms

In this section, we present additional analysis that provides more insight into the mechanisms through which the temperature–homicide relationship arises, and the circumstances under which RTC laws attenuate the temperature–homicide relationship.

Lethality and Displacement Effects: We begin by documenting that our main effects are driven by homicides involving a firearm. Homicides involving a firearm account for almost 60% of all homicides in the data, although we caveat that this number may be coded with error; whether the information is available depends on whether police departments reported this information in the data they uploaded to the FBI, and they might not do so consistently. Panel A of Table 4 shows that across both research designs, the differential temperature–homicide relationship in more-prohibitive policy regimes is driven by homicides involving guns. These findings provide support for the interpretation that our main estimates reflect the causal effect of gun laws on the temperature–homicide relationship. We note that the baseline temperature–homicide relationship is also stronger when a firearm is involved, consistent with firearms being more lethal (Table C1).

In light of this, it is interesting to explore the extent to which more-prohibitive gun laws result in displacement from "would-be" temperature-driven homicides to more temperature–driven aggravated assaults. On average, we estimate that a one-degree Celsius increase in temperature is associated with an additional 0.00669 aggravated assaults per 100,000 people, an increase of 0.8% compared to the mean (Table C2). Of this increase, 76% is driven by aggravated assaults that do not involve a firearm. To the extent that this displacement effect exists, we would expect it to offset any attenuating effects of more-prohibitive policy regimes. Consistent with this, we do not estimate a differential temperature–homicide relationship in more-prohibitive policy regimes (Panel B, Table 4). The estimated coefficients on the differential temperature–aggravated assault relationship are negative, though small and statistically insignificant, and so we are not able to provide conclusive evidence of a displacement effect. It is possible that the statistically insignificant effect on aggravated assaults reflect a net zero, whereby an increase in aggravated firearm assaults (displaced homicides) is offset by a broader policy-driven reduction in other aggravated firearm assaults, attenuating the aggregate reduction in violent crime.

Social Interactions vs. Impulse Control/Aggression: Next, we explore the mechanisms through which temperature drives our results. Broadly, temperature could affect violent behavior in two primary ways: (1) behavioral channels, e.g., increased aggression or reduced impulse control and (2) social channels, e.g., more social interaction on warmer days.[11]

First, we consider what can be learned from the precipitation–homicide relationship. Arguably, days with more precipitation should only affect violence through reduced social interactions. Consistent with this, we estimate that more precipitation is associated with fewer homicides (Table 2). In our main analysis, however, the *Precipitation* × *More-Prohibitive* coefficient is small and statistically insignificant (Table 3). This suggests that, on the margin, gun laws are not affecting the types of homicide offense that are sensitive to precipitation; i.e., those that arise in contexts with greater social interaction.

Second, we consider how our estimates vary between locations. If higher temperatures are changing people's movement patterns in a way that increases social interaction, we would expect them to leave the home to go outside or another location when it is warmer outside. To explore this, we look at the temperature–homicide relationships for homicides that occur at home, outside, or in other locations. In the NIBRS data, 62% of homicides occur in the home, 20% occur outside, and 18% occur at a different indoor location. Table C3 reports the baseline temperature–homicide relationships for each location. We see that, across all specifications, the strongest temperature–homicide relationship is within the home.

[11] It has been argued that the behavioral channel results from changes in the autonomic nervous system (ANS). The ANS is divided into two subsystems: the parasympathetic nervous system (PSNS) and the sympathetic nervous system (SNS). The PSNS is known to be responsible for stimulating arousal, and is complementary to the SNS, which is responsible for stimulating activities associated with the fight-or-flight response.

A one-degree Celsius increase in temperature is associated with an additional 0.0000579 homicides per 100,000 people at home and 0.0000432 homicides per 100,000 people outside. We do not estimate a statistically significant temperature–homicide relationship in other locations after location fixed effects are included in the empirical specification. Panel A of Table 5 documents that across both research designs, more-prohibitive policy regimes are associated with attenuated temperature–homicide relationships in all locations. The existence of an outdoor and home effect provides additional support for the hypothesis that increased aggression or lower impulse control are important mechanisms.

Third, we consider the extent to which variation in the temperature–homicide relationship throughout the day may provide insights into the underlying mechanisms. For example, we might expect the social interaction mechanism to be distributed more evenly throughout the day than impulse control/aggression mechanisms. If anything, we might expect social interactions to be more likely and impulse control and aggression effects to be less likely, in the morning before the heat of the day. Table C4 shows that hotter days are associated with more homicides in the morning, afternoon, and evening. In the data, 16% of homicides happen in the morning between 6 am and noon, 20% of homicides happen in the afternoon between noon and 6pm, and 64% of homicides happen at night between 6 pm and 6 am. Compared to the mean, we estimate that the baseline temperature–homicide relationship is most responsive in the afternoon. Across both research designs, we do not estimate a statistically significant differential effect in the temperature–homicide relationship for homicides that occur in the cooler morning hours, but do estimate differential effects in the afternoon and evening (Panel B, Table 5). These findings provide further support for the empirical relevance of impulse control/aggression mechanisms.

6 Discussion

In this paper, we explore the relationship between temperature, gun control laws, and violent crime, specifically homicides. Using two different research designs, our findings show that more-prohibitive policy regimes are associated with an attenuated temperature–homicide relationship.

As policy regimes have become less-prohibitive over time we calculate that the consequences of temperature on homicide have become more important. Holding fixed the population in 2016, but applying the 1991 policy regime — 23% of the population — we calculate that a one-degree increase in temperature would have been associated with 97 more homicides than if more-prohibitive laws were in place. By contrast holding fixed the population living in less-prohibitive states in 2016 — 72% — we calculate that a one-degree increase in temperature would be associated with 299 more homicides than if more-prohibitive laws were in place. The combination of rising average temperatures alongside a trajectory towards less prohibitive policy regimes suggest that temperature–driven homicides are likely to become more relevant, unless we are able to disrupt the influence of external factors in shaping violent behavior.

Using a social cost of homicide of \$11.3 million (\$2021) from McCollister, French and Fang (2010), we calculate that aggregate willingness to pay to reduce the risk of temperature-driven homicides would be \$3.380 billion/1°C.[12] This is comparable in magnitude to the expected social benefits associated with: 12,832 additional police officers (Chalfin and McCrary, 2018);[13] 411 additional substance abuse treatment facilities (Bondurant, Lindo and Swensen, 2018);[14] 7,052 mental healthcare facilities (Deza, Maclean and Solomon, 2022);[15]

[12] \$3.380 billion/1°C = $\sum_{j,2016}$ 365.25 days × -0.000349 homicides per day per 100,000 people × the number of people living in jurisdiction, j of less-prohibitive state, s, in 2016 × \$11.3 million.

[13] We use Chalfin and McCrary (2018)'s benefit cost ratio of 1.63. We assume a cost per "fully-fledged" police officer of \$161,532 in \$2021. Therefore, the estimated social benefit per officer is \$263,397. \$3.380 billion/\$263,397= 12,832 additional officers.

[14] Bondurant, Lindo and Swensen (2018) estimate that an additional substance abuse treatment facility would be associated with an expected social benefit of \$8.22 million in \$2021, including avoided drug-related mortality and crime, with a benefit cost ratio of 6.95. \$3.380 billion/\$8.22 million = 411.

[15] Deza, Maclean and Solomon (2022) estimate that opening ten additional mental healthcare offices

expanding programs like the Rapid Employment and Development Initiative in Chicago — which provided an 18-month job alongside cognitive behavioral therapy and other social support — to an additional 3,481 participants (Bhatt et al., forthcoming).[16]

We note caveats. First, our findings speak only to the effects of RTC laws on temperature-driven homicides. Temperature-driven criminal activity is impulsive, not premeditated. Our results do not speak to the effects of RTC laws on premeditated crimes or other impulsive crimes. Second, a causal interpretation of our results requires the assumption that there are no other differences between states (our "Difference-in-Temperature" design) or other concurrent changes over time alongside a policy change (our "Difference-in-Differences-in-Temperature" design) that also affect the temperature–homicide relationship. While confounding influences in this context are likely to be a strict subset of the confounding influences that affect preceding research, we cannot rule out their existence. Third, our analysis and discussion do not answer the normative question of whether more-prohibitive laws should be implemented. Our analysis does not provide evidence on the costs to gun owners and there are reasons to believe the costs would be nontrivial.[17] Rather, we have shown that temperature is an empirically relevant and meaningful driver of violent crime. If less-prohibitive concealed-carry laws increase other impulsive homicides and premeditated homicides, temperature-driven homicides will exacerbate the social cost of concealed-carry laws. If less-prohibitive concealed-carry laws deter other impulsive homicides and premeditated homicides, temperature-driven homicides will offset the social benefits of concealed-carry laws. To the extent that temperature-driven homicides and other impulse homicides account

would be associated with a \$4.793 million reduction in crime costs in \$2021. Opening one office would deliver \$479,300 in benefits. \$3.380 billion/\$479,300 = 7,052 facilities.

[16] Bhatt et al. (forthcoming) calculate that participation in the READI program in Chicago could be expected to generate \$970,890 in expected social benefits per participant (\$2021) at a cost of \$48,756 (\$2021) – a benefit–cost ratio of 20. \$3.380 billion/\$970,890 = 3,481 participants.

[17] According to recent Gallup poll statistics, 42% of the population believes that gun control should remain as is or become less strict (Gallup, 2023). By revealed preference, gun rights lobbyists have, on average, spent more than \$11 million each year over the past decade to reduce restrictions on the ability of individuals to buy, carry, or use a gun (OpenSecrets, 2023). More concretely, Moshary, Shapiro and Drango (2023) provide evidence to suggest that demand for firearms is inelastic and that the cost to gun owners of restricting access captured by reduced consumer surplus may be substantial.

for a significant share of all homicides, we may expect there to be greater heterogeneity in the overall effects of laws, regulations, and policies over time and space. When external factors, such as temperature, are an important influence of economic and social outcomes, they will reduce the external validity of policy evaluations. Understanding the extent to which we can influence external factors that shape violent behavior and other welfare-relevant outcomes remains an important avenue for future research.

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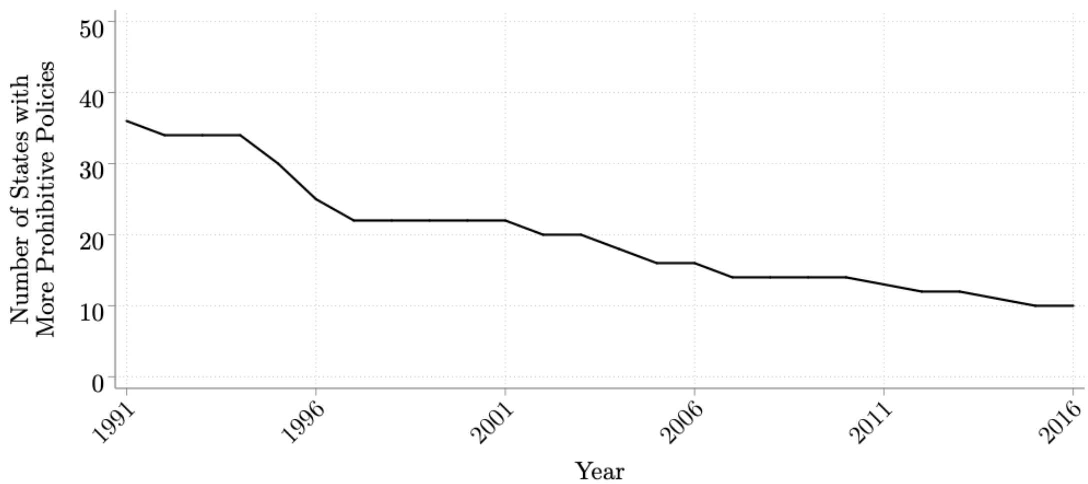
Figures and Tables

Figure 1: The Evolution of More-Prohibitive Concealed Carry Laws in the United States (1991-2016)



Notes: The policy data was hand coded by Chris Poliquin and coauthors using Cook and Ludwig's *Evaluating Gun Policy*, Vernick and Hepburn's *State and Federal Gun Laws: Trends for 1970-1999* as well as state statutes and session laws.

Table 1: Descriptive Statistics

	(1) All	(2) More Prohibited	(3) Less Prohibited	(4) Difference (2-3)	(5) Observations
Homicides per 100,000 people	0.0121	0.00921	0.0131	-0.0039*	13,495,334
	(0.00195)	(0.00275)	(0.0018)	(0.00204)	
Gun Homicides 100,000 people	0.00698	0.005	0.00763	-0.00264*	13,495,334
	(0.00136)	(0.00185)	(0.00128)	(0.00138)	
Non-Gun Homicides 100,000 people	0.00517	0.00421	0.00548	-0.00127*	13,495,334
	(0.000595)	(0.000911)	(0.00053)	(0.000692)	
Aggravated Assaults 100,000 people	0.894	0.929	0.882	0.0464	13,495,334
	(0.149)	(0.177)	(0.154)	(0.128)	
Population	30,644	27,498	31,682	-4,185	13,495,334
	(2,108)	(2,174)	(2,514)	(3,035)	
Average Daily Temperature (°C)	11.98	11.04	12.29	-1.25*	13,495,334
	(0.745)	(0.625)	(0.824)	(0.655)	
Total Daily Precipitation (mm)	2.90	2.96	2.88	0.078	13,495,334
	(0.151)	(0.20)	(0.17)	(0.212)	

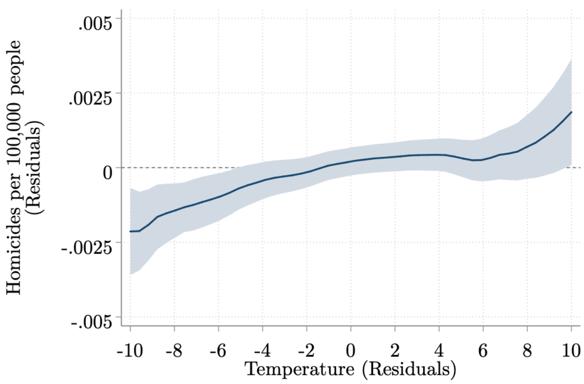
Notes: Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table 2: The Baseline Temperature–Homicide Relationship

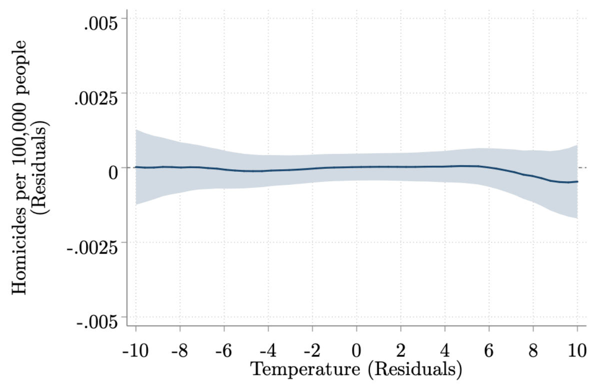
	Homicides per 100,000 People			
	(1)	(2)	(3)	(4)
Panel A: All States and Years				
Temperature (°C)	0.000213***	0.000688***	0.000170***	0.000105***
	(0.0000218)	(0.0000652)	(0.0000477)	(0.0000348)
Precipitation (mm)	-0.0000276	-0.0000609***	-0.0000506***	-0.0000497**
	(0.0000205)	(0.0000209)	(0.0000208)	(0.0000203)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.012	0.012	0.012	0.012
Panel B: "More-Prohibitive" Policy Regimes				
Temperature (°C)	0.000162***	0.000430***	0.00000121	-0.0000433
	(0.0000322)	(0.0000825)	(0.0000557)	(0.0000510)
Precipitation (mm)	-0.0000324	-0.0000627**	-0.0000383	-0.0000469
	(0.0000303)	(0.0000308)	(0.0000300)	(0.0000304)
Observations	3,349,396	3,349,396	3,349,396	3,349,396
Dependent Variable Mean	0.0092	0.0092	0.0092	0.0092
Panel C: "Less-Prohibitive" Policy Regimes				
Temperature (°C)	0.000219***	0.000657***	0.000225***	0.000155***
	(0.0000236)	(0.0000683)	(0.0000593)	(0.0000438)
Precipitation (mm)	-0.0000225	-0.0000526**	-0.0000544**	-0.0000504**
	(0.0000257)	(0.0000262)	(0.0000259)	(0.0000256)
Observations	10,145,938	10,145,938	10,145,938	10,145,938
Dependent Variable Mean	0.013	0.013	0.013	0.013
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: The outcome variable is the number of homicides per 100,000 people. The unit of analysis is a jurisdiction-day. Homicide is defined as nonnegligent homicide. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Figure 2: Differences in the Temperature–Homicide Relationship Between More-Prohibitive and Less-Prohibitive Right-to-Carry States



(a) Less-Prohibitive Policy Regimes



(b) More-Prohibitive Policy Regimes

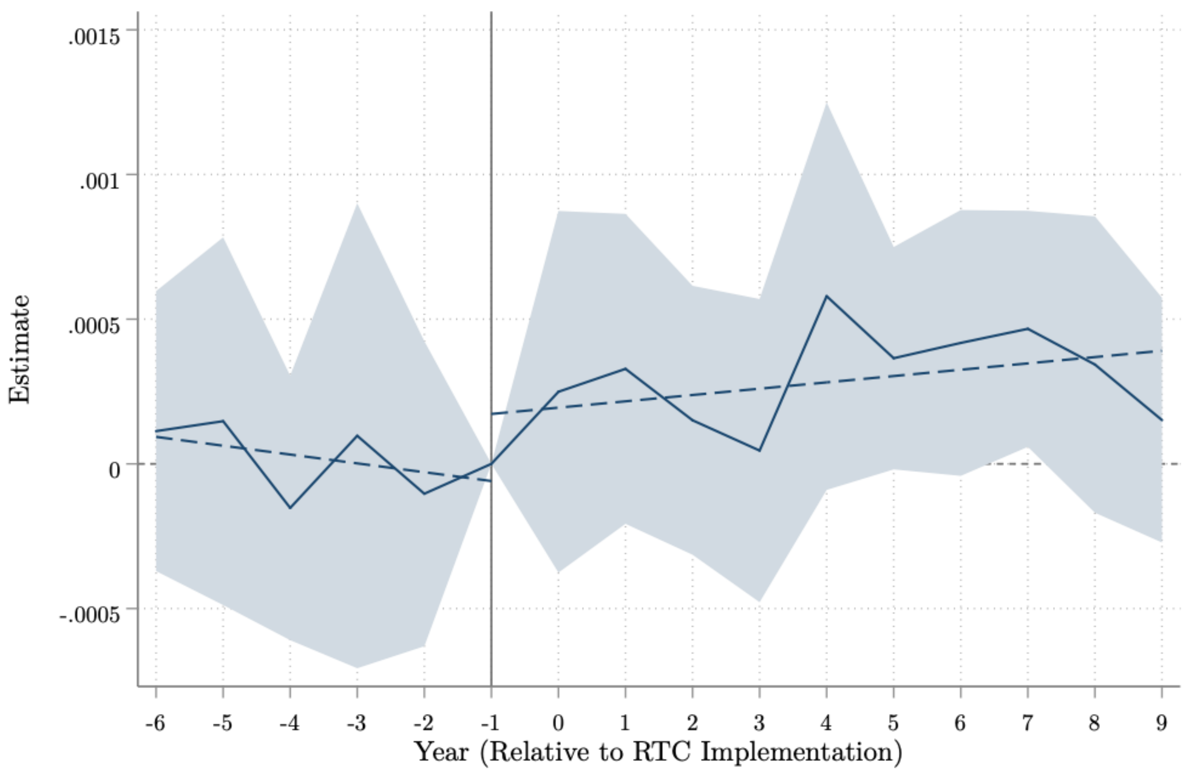
NOTES: Homicides per 100,000 people and daily average temperature are separately regressed on daily precipitation, jurisdiction-month-year, week-of-year, and day-of-week fixed effects. Figure (a) plots the semi-parametric relationship between these regressions for the jurisdiction-day observations that are exposed to less-prohibitive concealed-carry laws during our sample. Figure (b) plots the semi-parametric relationship between these regressions for the jurisdiction-day observations that are exposed to more-prohibitive concealed-carry laws during our sample. These figures correspond to column (4) of Table 2.

Table 3: Concealed Carry Laws and the Temperature–Homicide Relationship

	Homicides per 100,000 People				
	(1)	(2)	(3)	(4)	(5)
	DiT	DiT	DiDiT	DiDiT	DiDiT
Temperature × More Prohibitive	-0.000511**	-0.000562***	-0.000332**	-0.000349***	-0.000216*
	(0.000200)	(0.000203)	(0.000159)	(0.000112)	(0.000115)
Precipitation × More Prohibitive	-0.0000256	-0.0000354	0.00000648	0.00000724	-0.000238
	(0.0000482)	(0.0000505)	(0.0000687)	(0.0000751)	(0.000161)
Observations	13,495,334	12,979,068	13,495,334	13,495,334	8,501,265
Dependent Variable Mean	0.012	0.012	0.012	0.012	0.012
Month-Year Fixed Effects	Yes	Yes	–	–	–
Month-specific "More Prohibitive" Controls	Yes	Yes	–	–	–
State-Month-Year Fixed Effects	No	No	Yes	–	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Donut Specification	No	Yes	No	No	No
Aggregation of Cohort-Specific Estimates	No	No	No	No	Yes
Week-of-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is the number of homicides per 100,000 people. The unit of analysis is a jurisdiction-day. Homicide is defined as nonnegligent homicide. "More Prohibitive" is a time-varying indicator for whether the state is in a "More Prohibitive" concealed carry policy environment. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Column (1) presents estimates from our Differences-in-Temperature specification (Equation 1). Column (2) continues with the same specification as column (1), but drops the years either side of concealed carry policy changes. Column (3) presents estimates from our Difference-in-Differences-in-Temperature specification (Equation 2). Column (4) presents estimates from our Difference-in-Differences-in-Temperature specification (Equation 3). Column (5) represents a weighted average of cohort-specific estimates, using the specification in column (4), to address staggered timing concerns. Weather controls include month-year-specific temperature and rainfall coefficients (all specifications), state-specific temperature and rainfall coefficients (column 3), and jurisdiction-specific temperature and rainfall coefficients (columns 4-5). The DiT specifications (columns 1 and 2) also control for month-specific "More Prohibitive" coefficients. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between rainfall, temperature, and homicides. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Figure 3: Event Study of the Differential Effect of Right-to-Carry Laws on the Temperature–Homicide Relationship



NOTES: This figure plots estimates of the daily temperature–homicide relationship, averaged over the 12-month periods before and after the introduction of less-prohibitive concealed-carry laws. Homicides per 100,000 people is regressed on daily average temperature interacted with indicator variables for each 12 month period before and after the implementation of the policy. The coefficients are estimated using the following specification: $y_{j,d} = \alpha_{j,m(d)} + \gamma_{m(d)} f(w_{j,d}) + \gamma_j f(w_{j,d}) + \beta_\tau \sum_{-\tau}^{\tau} f(w_{j,d}) \times \text{More-Prohibitive}_{s(j),\tau} + \epsilon_{j,d}$. The figure plots the coefficients on the interaction terms between temperature and the indicator variables from 6 years before until 9 years after the policy implementation.

Table 4: The Differential Temperature–Homicide and Temperature–Assault Relationships (Firearms vs. Non-Firearms)

	DiT Analysis			DiDiT Analysis		
	(1) All	(2) Firearms	(3) Non-Firearms	(4) All	(5) Firearms	(6) Non-Firearms
Panel A: Homicides per 100,000 People						
Temperature × More-Prohibitive	-0.000511** (0.000200)	-0.000352*** (0.000121)	-0.000159* (0.0000868)	-0.000349*** (0.000112)	-0.000247*** (0.0000841)	-0.000102 (0.0000935)
Dependent Variable Mean	0.012	0.0069	0.0051	0.012	0.0069	0.0051
Panel B: Aggravated Assaults per 100,000 People						
Temperature × More-Prohibitive	-0.0283 (0.01981)	-0.00626 (0.003809)	-0.0220 (0.01618)	-0.000120 (0.00161)	-0.000105 (0.000476)	-0.0000148 (0.00140)
Dependent Variable Mean	0.893	0.142	0.751	0.893	0.142	0.751
Observations	13,495,334	13,495,334	13,495,334	13,495,334	13,495,334	13,495,334
Month-Year Fixed Effects	Yes	Yes	Yes	–	–	–
Month-specific "More-Prohibitive" Controls	Yes	Yes	Yes	–	–	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In Panel A the outcome variable is the number of nonnegligent homicides per 100,000 people. In panel B the outcome variable is the number of aggravated assaults per 100,000 people. Columns (1) and (4) report baseline coefficients for our DiT and DiDiT specifications. Columns (2) and (5) use crimes involving firearms as the outcome variable. Columns (3) and (6) use crimes not involving firearms as the outcome variable. The unit of analysis is a jurisdiction-day. "More-Prohibitive" is a time-varying indicator for whether the state is in a "More-Prohibitive" concealed-carry policy environment. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and "More-Prohibitive" (all specifications), month-year-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (columns 4-6). The DiT specifications (columns 1-3) also include controls for month-specific "More-Prohibitive" coefficients. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and violent crime. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table 5: The Differential Temperature–Homicide Relationship (Time of Day and Location)

	Homicides per 100,000 People					
	DiT Analysis			DiDiT Analysis		
	(1) At Home	(2) Outside	(3) Other	(4) At Home	(5) Outside	(6) Other
Panel A: Location						
Temperature × More-Prohibitive	-0.000180*	-0.000142**	-0.000189**	-0.000173**	-0.0000972*	-0.0000784
	(0.0000952)	(0.0000622)	(0.0000839)	(0.0000858)	(0.0000499)	(0.0000494)
Dependent Variable Mean	0.0073	0.0027	0.0021	0.0073	0.0027	0.0021
	Homicides per 100,000 People					
	DiT Analysis			DiDiT Analysis		
	(1) 6am - 12pm	(2) 12pm - 6pm	(3) 6pm - 6am	(4) 6am - 12pm	(5) 12pm - 6pm	(6) 6pm - 6am
Panel B: Time of Day						
Temperature × More-Prohibitive	-0.0000298	-0.000112**	-0.000309**	0.0000325	-0.000130*	-0.000241*
	(0.0000269)	(0.0000460)	(0.000143)	(0.0000354)	(0.0000772)	(0.000132)
Dependent Variable Mean	0.0019	0.0024	0.0075	0.0019	0.0024	0.0075
Observations	13,495,334	13,495,334	13,495,334	13,495,334	13,495,334	13,495,334
Month-Year Fixed Effects	Yes	Yes	Yes	–	–	–
Month-specific “More-Prohibitive” Controls	Yes	Yes	Yes	–	–	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In Panel A the outcome variables are the number of the number of nonnegligent homicides per 100,000 people that were: committed at home (Columns 1 and 4); committed outside (Columns 2 and 5); committed in other locations (Columns 3 and 6). In Panel A the outcome variables are the number of nonnegligent homicides per 100,000 people that were: committed in the morning (Columns 1 and 4); committed in the afternoon (Columns 2 and 5); committed at night (Columns 3 and 6). The unit of analysis is a jurisdiction-day. “More-Prohibitive” is a time-varying indicator for whether the state is in a “More-Prohibitive” concealed-carry policy environment. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and “More-Prohibitive” (all specifications), month-year-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (columns 4-6). The DiT specifications (columns 1-3) also control for month-specific “More-Prohibitive” coefficients. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and homicides. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Online Appendices – Not for Publication

Contents

A The Baseline Relationship Between Temperature and Homicide

In this appendix we present results from additional analyses relating to the baseline temperature–homicide relationship. We first explore the extent to which there is a non-linear relationship between the temperature–homicide relationship. We do this in two ways. First, we estimate polynomial regressions between homicide and daily average temperature (up to 4th order),

$$f(temperature_{jdmy}) = \sum_{p=1}^{4} \beta_p t_{jdmy}^{p} \tag{A1}$$

The results of this analysis are presented in Figure A1. We do not see much evidence of a strong non-linear relationship. Moving from a linear relationship to a quadratic relationship has almost no effect on the predicted relationship. Incorporating a cubic term results in more of a concave relationship as temperatures increase, which remains in the 4th-order polynomial; however, in each specification, higher-order terms are always statistically insignificant, resulting in a noisier relationship as we move from a linear to a 4th-order polynomial relationship.

Second, we estimate 2-part linear splines of daily average temperature.

$$f(w_{jdmy}) = \beta_1 temperature_{jdmy} + \beta_2 (temperature_{jdmy} - \xi) \tag{A2}$$

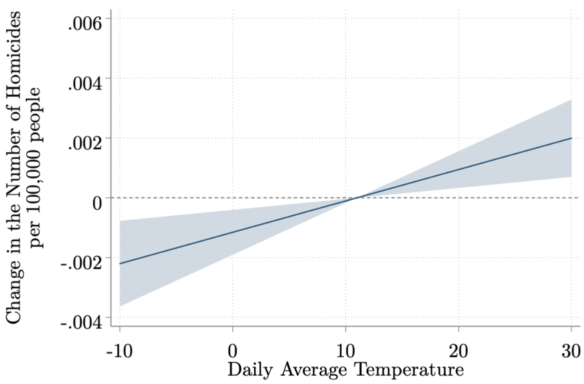
where ξ is the kinkpoint. We use a kinkpoint of 18°C,

$$(temperature_{jdmy} - \xi) = \begin{cases} temperature_{jdmy} - 18 & \text{if } temperature_{jdmy} \geq 18 \\ temperature_{jdmy} - 18 & \text{if } temperature_{jdmy} \leq 18 \end{cases}$$

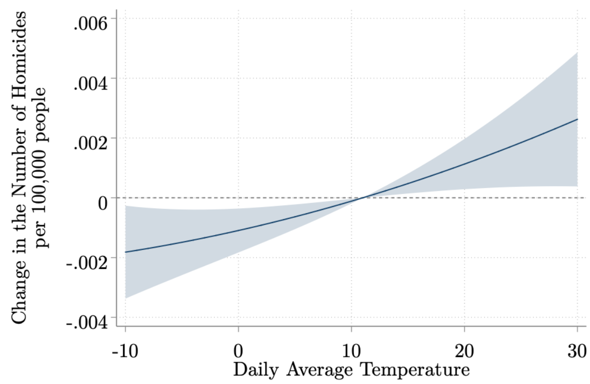
This approach is appealing for several reasons. First, the existing literature suggests that this simple functional form delivers results that are very similar to those estimated using more complicated functional forms. Second, other functional forms typically feature higher order terms, which in a panel setting means that the unit-specific mean re-enters the estimation, as is the case with using the quadratic functions (McIntosh and Schlenker, 2006). This raises omitted variable bias concerns, since identification in the panel models is no longer limited to location-specific variation over time.

We do not estimate a statistically significant change in the slope at the kink point. Figure A2 presents the result of this analysis. We cannot reject that the relationship between temperature and homicides per 100,000 people is linear, or at least locally linear. We are not the first paper to show this. In earlier work, Ranson (2014) shows that the temperature–violent-crime relationship in the United States is approximately linear. In contexts with a broader range of residual variation in temperatures, it is possible that a more complex response function exists. Our main analysis uses a linear specification, which is a reasonable fit, parsimonious, and reduces demands on the data when interaction terms are included.

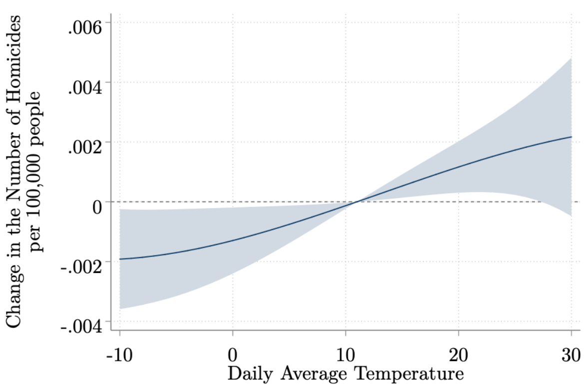
Figure A1: Exploring Non-Linearity in the Temperature–Homicide Relationship (Flexible Polynomials)



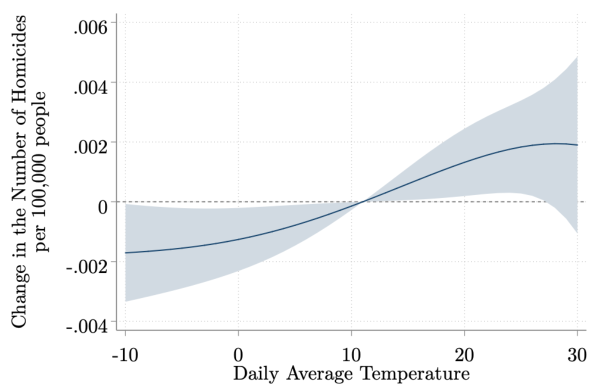
(a) Linear Relationship



(b) 2nd-order Polynomial



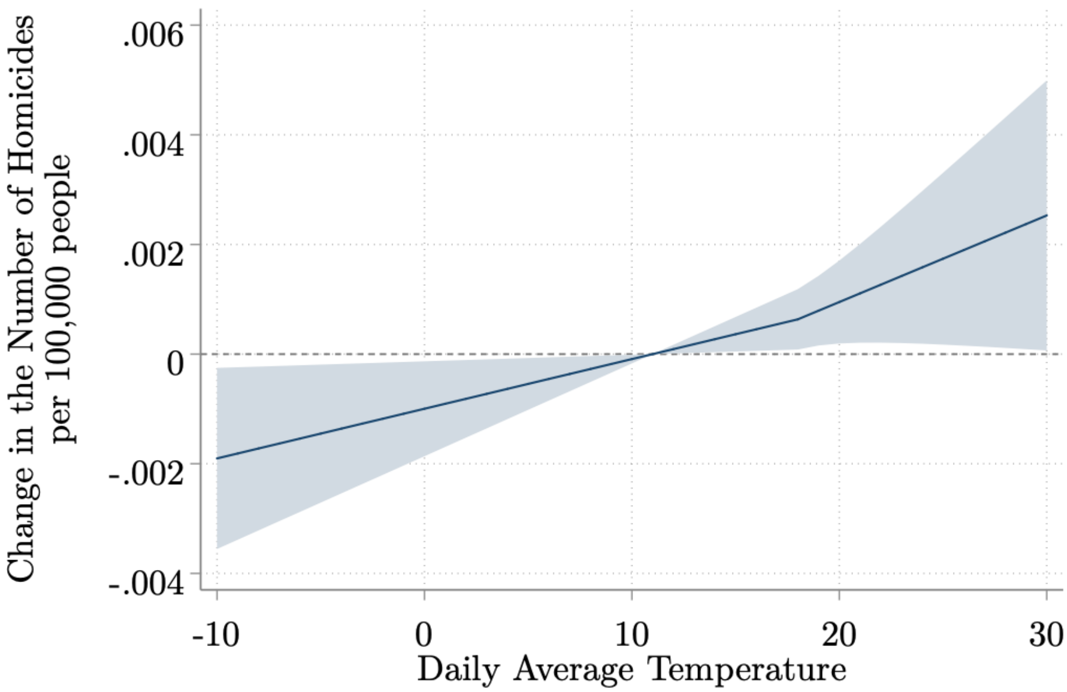
(c) 3rd-order Polynomial



(d) 4th-order Polynomial

NOTES: Estimates reflect the association between daily mean temperature and homicides per 100,000 people, relative to a day when the daily mean temperature is 11°C. Figure (a) plots the linear relationship. Figure (b) plots a 2nd-order polynomial relationship. Figure (c) plots a 3rd-order polynomial relationship. Figure (d) plots a 4th-order polynomial relationship. We control for daily precipitation in all specifications. Standard errors are clustered at the county level. The shaded areas reflect 95% confidence intervals.

Figure A2: Exploring Non-Linearity in the Temperature–Homicide Relationship (2-Part Linear Spline)



Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. Temperature is the daily mean temperature measured in degrees Celsius. The kinkpoint is 18°C. Estimates reflect the association between daily mean temperature on homicides per 100,000 people, relative to a day when the daily mean temperature is 11°C. We also control for daily precipitation measured in millimeters. Standard errors are clustered at the county level. Shaded areas reflect 95% confidence intervals.

Table A1: The Baseline Temperature–Homicide Relationship (Mean/Min/Max Temperature)

	Homicides per 100,000 People			
	(1)	(2)	(3)	
Panel A: Average Temperature				
Temperature (°C)	0.000213***	0.000688***	0.000170***	0.000105***
	(0.0000218)	(0.0000652)	(0.0000477)	(0.0000348)
Precipitation (mm)	-0.0000276	-0.0000609***	-0.0000506**	-0.0000497**
	(0.0000205)	(0.0000209)	(0.0000208)	(0.0000203)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.012	0.012	0.012	0.012
Panel B: Maximum Temperature				
Temperature (°C)	0.000204***	0.000619***	0.000133***	0.0000795**
	(0.0000204)	(0.0000557)	(0.0000413)	(0.0000309)
Precipitation (mm)	-0.00000971	-0.00000429	-0.0000392*	-0.0000429**
	(0.0000204)	(0.0000208)	(0.0000206)	(0.0000204)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.012	0.012	0.012	0.012
Panel C: Minimum Temperature				
Temperature (°C)	0.000209***	0.000621***	0.000163***	0.000103***
	(0.0000224)	(0.0000651)	(0.0000460)	(0.0000347)
Precipitation (mm)	-0.0000442**	-0.000107***	-0.0000622***	-0.0000569***
	(0.0000207)	(0.0000220)	(0.0000211)	(0.0000203)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.012	0.012	0.012	0.012
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. Temperature is defined as the daily mean (Panel A), daily maximum (Panel B), and daily minimum (Panel C) temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table A2: The Baseline Temperature–Homicide Relationship (Climate Differences)

	Homicides per 100,000 People			
	(1)	(2)	(3)	
Panel A: Drop Hot Climates				
Temperature (°C)	0.0000229*	0.0000536	0.0000422	0.0000901***
	(0.0000134)	(0.0000547)	(0.0000518)	(0.0000345)
Precipitation (mm)	-0.0000608***	-0.0000605***	-0.0000304*	-0.0000292
	(0.0000189)	(0.0000185)	(0.0000181)	(0.0000179)
Observations	9,002,210	9,002,210	9,002,210	9,002,210
Dependent Variable Mean	0.008	0.008	0.008	0.008
Panel B: Drop Temperate Climates				
Temperature (°C)	0.000279***	0.000762***	0.000143**	0.0000690
	(0.0000281)	(0.0000768)	(0.000065)	(0.0000457)
Precipitation (mm)	-0.00000703	-0.0000455	-0.0000417	-0.0000409
	(0.0000278)	(0.0000283)	(0.0000280)	(0.0000273)
Observations	8,995,758	8,995,758	8,995,758	8,995,758
Dependent Variable Mean	0.014	0.014	0.014	0.014
Panel C: Drop Cold Climates				
Temperature (°C)	0.000239***	0.000871***	0.000321***	0.000157***
	(0.0000264)	(0.0000786)	(0.0000557)	(0.0000468)
Precipitation (mm)	-0.0000381	-0.0000738***	-0.0000728***	-0.0000712***
	(0.0000247)	(0.0000254)	(0.0000251)	(0.0000246)
Observations	8,992,700	8,992,700	8,992,700	8,992,700
Dependent Variable Mean	0.014	0.014	0.014	0.014
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in mm. Climate terciles (Hot, Temperate, and Cold) are calculated using the long-run average temperature of each location. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table A3: The Baseline Temperature–Homicide Relationship (Seasonal Differences)

	Homicides per 100,000 People			
	(1)	(2)	(3)	(4)
Panel A: Drop Winter				
Temperature (°C)	0.000298***	0.000729***	0.000171***	0.000104**
	(0.0000320)	(0.0000778)	(0.0000625)	(0.0000427)
Precipitation (mm)	-0.0000131	-0.0000324	-0.0000353	-0.0000347
	(0.0000231)	(0.0000232)	(0.0000224)	(0.0000228)
Observations	10,334,062	10,334,062	10,334,062	10,334,062
Dependent Variable Mean	0.012	0.012	0.012	0.012
Panel B: Drop Spring				
Temperature (°C)	0.000180***	0.000672***	0.000158***	0.0000959**
	(0.0000206)	(0.0000715)	(0.0000604)	(0.0000420)
Precipitation (mm)	-0.0000218	-0.0000648**	-0.0000507**	-0.0000538**
	(0.0000249)	(0.0000252)	(0.0000252)	(0.0000251)
Observations	10,077,969	10,077,969	10,077,969	10,077,969
Dependent Variable Mean	0.012	0.012	0.012	0.012
Panel B: Drop Summer				
Temperature (°C)	0.000276***	0.000664***	0.000188***	0.000115***
	(0.0000278)	(0.0000594)	(0.0000430)	(0.0000372)
Precipitation (mm)	-0.0000408*	-0.0000706***	-0.0000517**	-0.0000397*
	(0.0000231)	(0.0000239)	(0.0000239)	(0.0000228)
Observations	9,952,812	9,952,812	9,952,812	9,952,812
Dependent Variable Mean	0.012	0.012	0.012	0.012
Panel B: Drop Fall				
Temperature (°C) 0.000198***	0.000697***	0.000163***	0.000105**	
	(0.0000216)	(0.0000705)	(0.0000559)	(0.0000407)
Precipitation (mm)	-0.0000408*	-0.0000781***	-0.0000668***	-0.0000731***
	(0.0000232)	(0.0000239)	(0.0000235)	(0.0000231)
Observations	10,121,159	10,121,159	10,121,159	10,121,159
Dependent Variable Mean	0.012	0.012	0.012	0.012
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in mm. 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. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table A4: The Baseline Temperature–Homicide Relationship (UCR Data)

	Homicides per 100,000 People			
	(1)	(2)	(3)	(4)
Panel A: All States and Years				
Temperature (°C)	0.00739***	0.0254***	0.00239***	0.00162***
	(0.000756)	(0.00206)	(0.000341)	(0.000249)
Precipitation (mm)	-0.0000275	-0.000161	-0.0000513	-0.0000118
	(0.000162)	(0.000178)	(0.0000568)	(0.0000374)
Observations	2,610,480	2,610,480	2,610,480	2,610,480
Dependent Variable Mean	0.297	0.297	0.297	0.297
Panel B: "More-Prohibitive" Policy Regimes				
Temperature (°C)	0.00810***	0.0325***	0.00245***	0.00133***
	(0.00194)	(0.00643)	(0.000746)	(0.000498)
Precipitation (mm)	-0.000563	-0.000723*	-0.000193	-0.0000416
	(0.000383)	(0.000420)	(0.000135)	(0.0000602)
Observations	1,026,090	1,026,090	1,026,090	1,026,090
Dependent Variable Mean	0.281	0.281	0.281	0.281
Panel C: "Less-Prohibitive" Policy Regimes				
Temperature (°C)	0.00681***	0.0211***	0.00237***	0.00183***
	(0.000368)	(0.00121)	(0.000279)	(0.000259)
Precipitation (mm)	0.000258***	0.000112**	0.0000275	0.0000083
	(0.0000537)	(0.0000563)	(0.0000443)	(0.0000469)
Observations	1,584,390	1,584,390	1,584,390	1,584,390
Dependent Variable Mean	0.306	0.306	0.306	0.306
Sample-Month Fixed Effects	No	Yes	–	–
State-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Year Fixed Effects	No	No	No	Yes

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-month. Temperature is defined as monthly average temperature measured in degrees Celsius. Precipitation is defined as total monthly precipitation measured in millimeters. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

B Main Results – Robustness Tests

Table B1: The Differential Temperature–Homicide Relationship (Mean/Min/Max Temperature)

	Homicides per 100,000 People					
	DiT Analysis			DiDiT Analysis		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Temperature × More-Prohibitive	-0.000511** (0.000200)			-0.000349*** (0.000112)		
Max Temperature × More-Prohibitive		-0.000335** (0.000154)			-0.000260* (0.000137)	
Min Temperature × More-Prohibitive			-0.000537*** (0.0001816)			-0.000151*** (0.0000534)
Observations	13,495,334	13,495,334	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.012	0.012	0.012	0.012	0.012	0.012
Month-Year Fixed Effects	Yes	Yes	Yes	–	–	–
Month-specific “More-Prohibitive” Controls	Yes	Yes	Yes	–	–	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. “More-Prohibitive” is a time-varying indicator for whether the state is in a “More-Prohibitive” concealed carry policy environment. The temperature variables are defined as daily mean, daily maximum, and daily minimum temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and “More-Prohibitive” (all specifications), month-year-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (columns 4-6). The DiT specifications (columns 1-3) also include control for month-specific “More-Prohibitive” coefficients. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and homicides. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table B2: The Differential Temperature–Homicide Relationship (Climate Differences)

	Homicides per 100,000 People		
	(1) Drop Hot	(2) Drop Temperate	(3) Drop Cold
Panel A: DiT Approach			
Temperature × More-Prohibitive	-0.000151	-0.000585**	-0.000628**
	(0.0001132)	(0.0002283)	(0.0002546)
Panel B: DiDiT Approach			
Temperature × More-Prohibitive	-0.000238***	-0.000395***	-0.000464***
	(0.0000747)	(0.000147)	(0.000161)
Observations	9,002,210	8,995,758	8,992,700
Dependent Variable Mean	0.008	0.014	0.014

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. "More-Prohibitive" is a time-varying indicator for whether the state is in a "More-Prohibitive" concealed carry policy environment. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and "More-Prohibitive" (all specification), month-year-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (Panel B). The DiT specifications (Panel A) also include month fixed effects and control for month-specific "More-Prohibitive" coefficients. The DiDiT specifications (Panel B) also include jurisdiction-by-month fixed effects. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and homicides. Climate terciles (Hot, Temperate, and Cold) are calculated using the long-run average temperature of each location. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table B3: The Differential Temperature–Homicide Relationship (Seasonal Differences)

	Homicides per 100,000 People			
	(1) Drop Winter	(2) Drop Spring	(3) Drop Summer	(4) Drop Fall
Panel A: DiT Approach				
Temperature × More-Prohibitive	-0.000509**	-0.000534**	-0.000544***	-0.000457**
	(0.000206)	(0.0002228)	(0.0001921)	(0.0001945)
Panel B: DiDiT Approach				
Temperature × More-Prohibitive	-0.000351***	-0.000348***	-0.000424***	-0.000261
	(0.000124)	(0.000106)	(0.000146)	(0.000169)
Observations	10,334,062	10,077,969	9,952,812	10,121,159
Dependent Variable Mean	0.012	0.012	0.012	0.012

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. "More-Prohibitive" is a time-varying indicator for whether the state is in a "More-Prohibitive" concealed carry policy environment. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and "More-Prohibitive" (all specifications), month-year-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (Panel B). The DiT specifications (Panel A) also include month fixed effects and control for month-specific "More-Prohibitive" coefficients. The DiDiT specifications (Panel B) also include jurisdiction-by-month fixed effects. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and homicides. 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. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table B4: The Differential Temperature–Homicide Relationship (Binary Outcome)

	Any Homicide	
	(1) DiT	(2) DiDiT
Temperature × More-Prohibitive	-0.000141*** (0.0000396)	-0.0000391** (0.0000179)
Observations	13,495,334	13,495,334
Dependent Variable Mean	0.0037	0.0037
Month-Year Fixed Effects	Yes	–
Month-specific "More-Prohibitive" Controls	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	Yes
Weather Controls	Yes	Yes
Week-of-Year Fixed Effects	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes

Notes: The outcome variable is a binary indicator for whether any nonnegligent homicides occurred on day d. The unit of analysis is a jurisdiction-day. "More-Prohibitive" is a time-varying indicator for whether the state is in a "More-Prohibitive" concealed carry policy environment. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and "More-Prohibitive" (all specifications), month-year-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (Column 2). The DiT specification (Column 1) also includes month fixed effects and controls for month-specific "More-Prohibitive" coefficients. The DiDiT specifications (Column 2) also includes jurisdiction-by-month fixed effects. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and homicides. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table B5: The Differential Temperature–Homicide Relationship (County-Day Unit)

	Homicides per 100,000 People	
	(1) DiT	(2) DiDiT
Temperature × More-Prohibitive	-0.000361** (0.000167)	-0.000292** (0.000130)
Observations	5,942,581	5,942,581
Dependent Variable Mean	0.013	0.013
Month-Year Fixed Effects	Yes	–
Month-specific “More-Prohibitive” Controls	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	Yes
Weather Controls	Yes	Yes
Week-of-Year Fixed Effects	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a county-day. “More-Prohibitive” is a time-varying indicator for whether the state is in a “More-Prohibitive” concealed carry policy environment. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and “More-Prohibitive” (all specifications), month-year-specific temperature and precipitation coefficients (all specifications) and county-specific temperature and precipitation coefficients (Column 2). The DiT specification (Column 1) also includes month fixed effects and controls for month-specific “More-Prohibitive” coefficients. The DiDiT specifications (Column 2) also includes county-by-month fixed effects. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and homicides. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table B6: The Differential Temperature–Homicide Relationship (UCR Data)

	Homicides per 100,000 People			
	(1) DiT	(2) DiT	(3) DiDiT	(4) DiDiT
Temperature × More-Prohibitive	0.00424 (0.00514)	0.00900** (0.00411)	-0.00223*** (0.000861)	-0.00176** (0.000693)
Observations	1,141,824	2,610,480	1,141,824	2,610,480
Dependent Variable Mean	0.252	0.297	0.252	0.297
NIBRS restriction	Yes	No	Yes	No
Month-Year Fixed Effects	Yes	Yes	–	–
Month-specific “More-Prohibitive” Controls	Yes	Yes	–	–
Jurisdiction-Year Fixed Effects	No	No	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes

Notes: The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-month. “More-Prohibitive” is a time-varying indicator for whether the state is in a “More-Prohibitive” concealed carry policy environment. Temperature is defined as monthly average temperature measured in degrees Celsius. Precipitation is defined as total monthly precipitation measured in mm. Weather controls include the interaction between Precipitation and “More-Prohibitive” (all specifications), month-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (columns 3 and 4). The DiT specifications (columns 1 and 2) also include month fixed effects and control for month-specific “More-Prohibitive” coefficients. The DiDiT specifications (columns 3 and 4) also include jurisdiction-by-year fixed effects. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table B7: Other Regulations and the Temperature–Homicide Relationship

	Homicides per 100,000 People				
	(1)	(2)	(3)	(4)	(5)
Panel A: DiT					
Temperature × More-Prohibitive	-0.000251***				-0.000420**
	(0.0000647)				(0.000213)
Temperature × Waiting Period		-0.000603***			-0.0000340
		(0.000184)			(0.000178)
Temperature × Background Checks			-0.000416		-0.000397
			(0.000268)		(0.000264)
Temperature × std(# of Gun Laws)				-0.000241**	0.00000794
				(0.000101)	(0.000103)
Panel B: DiDiT					
Temperature × More-Prohibitive	-0.000349***				-0.000368***
	(0.000112)				(0.000128)
Temperature × Waiting Period		-0.000238			-0.000263*
		(0.000171)			(0.000155)
Temperature × Background Checks			-0.000390		-0.000429
			(0.000414)		(0.000325)
Temperature × std(# of Gun Laws)				-0.000139	0.0000677
				(0.000311)	(0.000280)
Observations	13,495,334	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.012	0.012	0.012	0.012	0.012

The outcome variable is the number of nonnegligent homicides per 100,000 people. The unit of analysis is a jurisdiction-day. “More-Prohibitive” is a time-varying indicator for whether the state is in a “More-Prohibitive” concealed carry policy environment. “Waiting Period” is a time-varying indicator for whether explicit waiting periods, permit requirements to purchase a gun, or the Brady Act between 1994 and 1998, were in effect during a state-month. “Background Check” is a time-varying indicator for whether a background check (private sale or dealership checks) was required in a state-month. “std(# of Gun Laws)” is a standardized (mean zero, standard deviation one) measure of the number of prohibiting gun laws implemented by each state in a given year, provided by https://www.statefirearmlaws.org/national-data. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Weather controls include the interaction between Precipitation and “More-Prohibitive” (all specifications), month-year-specific temperature and precipitation coefficients (all specifications) and jurisdiction-specific temperature and precipitation coefficients (Panel B). The DiT specifications (Panel A) also include month fixed effects and control for month-specific “More-Prohibitive” coefficients. The DiDiT specifications (Panel B) also include jurisdiction-by-month fixed effects. In all specifications, we include week-of-year and day-of-week fixed effects to account for seasonality in the relationship between precipitation, temperature, and homicides. Standard errors are clustered at the state level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

C Exploring Mechanisms – Additional Results and Robustness Tests

Table C1: The Baseline Temperature–Homicide Relationship (Firearms vs. Non-Firearms)

	Homicides per 100,000 People			
	(1)	(2)	(3)	(4)
Panel A: Homicides involving a Firearm				
Temperature (°C)	0.000150***	0.000481***	0.000120***	0.0000653***
	(0.0000160)	(0.0000484)	(0.0000381)	(0.0000233)
Precipitation (mm)	-0.0000199	-0.0000428***	-0.0000394**	-0.0000356**
	(0.0000158)	(0.0000161)	(0.0000156)	(0.0000152)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0069	0.0069	0.0069	0.0069
Panel B: Homicides not involving a Firearm				
Temperature (°C)	0.0000637***	0.000207***	0.0000504*	0.0000396
	(0.0000111)	(0.0000272)	(0.0000261)	(0.0000247)
Precipitation (mm)	-0.00000768	-0.0000181	-0.0000111	-0.0000141
	(0.0000125)	(0.0000127)	(0.0000132)	(0.0000136)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0051	0.0051	0.0051	0.0051
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: In Panel A the outcome variable is the number of nonnegligent homicides per 100,000 people involving a firearm. In Panel B the outcome variable is the number of nonnegligent homicides per 100,000 not involving a firearm. The unit of analysis is a jurisdiction-day. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table C2: The Baseline Temperature–Aggravated Assault Relationship

	Aggravated Assaults per 100,000 People			
	(1)	(2)	(3)	(4)
Panel A: All Aggravated Assaults				
Temperature (°C)	0.0167***	0.0422***	0.00695***	0.00669***
	(0.00139)	(0.00383)	(0.00190)	(0.00112)
Precipitation (mm)	-0.00164***	-0.00290***	-0.00238***	-0.00249***
	(0.000577)	(0.000598)	(0.000372)	(0.000401)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.893	0.893	0.893	0.893
Panel B: Aggravated Assaults involving a Firearm				
Temperature (°C)	0.00378***	0.0110***	0.00240***	0.00158***
	(0.000330)	(0.000893)	(0.000432)	(0.000342)
Precipitation (mm)	-0.000269	-0.000696***	-0.000535***	-0.000553***
	(0.000236)	(0.000241)	(0.000188)	(0.000205)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.142	0.142	0.142	0.142
Panel C: Aggravated Assaults not involving a Firearm				
Temperature (°C)	0.0129***	0.0312***	0.00455***	0.00512***
	(0.00111)	(0.00306)	(0.00161)	(0.000918)
Precipitation (mm)	-0.00137***	-0.00220***	-0.00185***	-0.00194***
	(0.000412)	(0.000433)	(0.000292)	(0.000276)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.751	0.751	0.751	0.751
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: In Panel A the outcome variable is the number of aggravated assaults per 100,000 people. In Panel B the outcome variable is the number of aggravated assaults per 100,000 people involving a firearm. In Panel C the outcome variable is the number of aggravated assaults per 100,000 not involving a firearm. The unit of analysis is a jurisdiction-day. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table C3: The Baseline Temperature–Homicide Relationship (Location)

	Homicides per 100,000 People			
	(1)	(2)	(3)	(4)
Panel A: Home				
Temperature (°C)	0.0000834***	0.000341***	0.0000888***	0.0000579**
	(0.0000126)	(0.0000303)	(0.0000277)	(0.0000257)
Precipitation (mm)	-0.0000126	-0.0000318**	-0.0000194	-0.0000148
	(0.0000152)	(0.0000157)	(0.0000159)	(0.0000160)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0073	0.0073	0.0073	0.0073
Panel B: Outside				
Temperature (°C)	0.0000728***	0.000182***	0.0000743***	0.0000432***
	(0.00000683)	(0.0000188)	(0.0000161)	(0.0000150)
Precipitation (mm)	-0.00000844	-0.0000135	-0.0000166*	-0.0000184**
	(0.00000870)	(0.00000874)	(0.00000867)	(0.0000093)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0024	0.0024	0.0024	0.0024
Panel B: Other Locations				
Temperature (°C)	0.0000570***	0.000165***	0.00000715	0.00000377
	(0.00000974)	(0.0000389)	(0.0000327)	(0.0000176)
Precipitation (mm)	-0.00000657	-0.0000155	-0.0000145	-0.0000165*
	(0.00000977)	(0.00000999)	(0.00000934)	(0.00000933)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0021	0.0021	0.0021	0.0021
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: In Panel A the outcome variable is the number of nonnegligent homicides per 100,000 people committed in the home. In Panel B the outcome variable is the number of nonnegligent homicides per 100,000 people committed outside. In Panel C the outcome variable is the number of nonnegligent homicides per 100,000 people committed in other locations. The unit of analysis is a jurisdiction-day. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

Table C4: The Baseline Temperature–Homicide Relationship (Time of Day)

	Homicides per 100,000 People			
	(1)	(2)	(3)	(4)
Panel A: Morning				
Temperature (°C)	0.0000229***	0.0000898***	0.0000196*	0.0000197*
	(0.00000540)	(0.0000114)	(0.0000114)	(0.0000118)
Precipitation (mm)	-0.00000114	-0.00000773	-0.00000442	-0.00000317
	(0.00000868)	(0.00000873)	(0.00000892)	(0.00000827)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0019	0.0019	0.0019	0.0019
Panel B: Afternoon				
Temperature (°C)	0.0000320***	0.000142***	0.0000504**	0.0000314*
	(0.00000604)	(0.0000186)	(0.0000196)	(0.0000163)
Precipitation (mm)	0.00000309	-0.0000037	-0.00000709	-0.00000728
	(0.00000909)	(0.00000933)	(0.00000977)	(0.0000102)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0024	0.0024	0.0024	0.0024
Panel B: Night				
Temperature (°C)	0.000154***	0.000456***	0.0000993**	0.0000442
	(0.0000168)	(0.0000483)	(0.0000402)	(0.0000278)
Precipitation (mm)	-0.0000237	-0.000044***	-0.0000328**	-0.0000328**
	(0.0000156)	(0.0000158)	(0.0000150)	(0.0000149)
Observations	13,495,334	13,495,334	13,495,334	13,495,334
Dependent Variable Mean	0.0075	0.0075	0.0075	0.0075
Month-Year Fixed Effects	No	Yes	–	–
State-Month-Year Fixed Effects	No	No	Yes	–
Jurisdiction-Month-Year Fixed Effects	No	No	No	Yes
Week-of-Year Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes

Notes: In Panel A the outcome variable is the number of nonnegligent homicides per 100,000 people committed in the morning. In Panel B the outcome variable is the number of nonnegligent homicides per 100,000 people committed in the afternoon. In Panel C the outcome variable is the number of nonnegligent homicides per 100,000 people committed at night. The unit of analysis is a jurisdiction-day. Temperature is defined as daily average temperature measured in degrees Celsius. Precipitation is defined as total daily precipitation measured in millimeters. Standard errors are clustered at the county level. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

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