Don't Lose Your Cool: Temperature and Gun-Violence in North America

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Abstract

Hotter temperatures due to climate change are expected to increase interpersonal violence. We find temperature increases gun-violence in Chicago not through hot days getting hotter but through cold days growing milder, which previous climate change damage predictions may overlook. For every season except summer, a 1°C warmer day results in 1.4% more gun-violence. Using data from automated crime reporting allows us to confirm criminal *behaviour* (rather than criminal *statistics* production) is temperature-increasing. We also find evidence that the COVID-19 pandemic and its lockdowns exacerbate the temperature-violence relationship, while positive shocks such as local NFL wins attenuate it.

"I pray thee, good Mercutio, let's retire, The day is hot, the Capulets are abroad, And if we meet we shall not 'scape a brawl, For these hot days is the mad blood stirring."

(William Shakespeare, 1597)

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1 Introduction

There is a well documented relationship between temperature and interpersonal violence. Previous research examines a different and compound causal relationship, temperature's effect on crime *statistic* production.[1] In this paper, we leverage city-wide always-on audio sensors to study and confirm a direct relationship between temperature and criminal behaviour. In order to gain this specificity, we are limited to measuring the specific behaviour of gun-violence, rather than crime more generally (such as in Ranson (2014)). Nonetheless, gun-violence is worthy of examination in and of itself, as not only are the personal consequences of a successful or failed shooting severe, our setting has multiple statutes which consider discharge of a firearm as a class 4, 1, or even X felony (with associated prison sentences ranging from 1-3, 4-5, and 6-30 years in addition to fines up to $25,000 regardless of any resulting personal injury).

We find that a 1°C warmer day is associated with a 1.4% increase in gun-violence - in all seasons except summer. The temperature-gun-violence relationship is exacerbated by negative psychological shocks (such as the COVID-19 pandemic and its lockdowns) and alleviated by positive psychological shocks (such as wins by the NFL's Bears). Our modern (2017-2024) and data rich setting, the City of Chicago, we take to be representative of large continental cities (Buffalo, Cleveland, Minneapolis, New York, Toronto) that currently enjoy a protective effect of cold temperatures that incapacitate the sort of criminal behaviour we examine and are predicted to lose under the most likely climate scenarios.

The literature we most directly contribute to examines the effect of temperature on crime. Here we discuss a non-exhaustive selection, highlighting differences between each and our analysis.

[1] Namely that a criminal behaviour must occur, which must be observed, which must be reported, which must be recorded as a statistic. Our use of automated data collection at the criminal behaviour stage allows us to speak directly to behaviour, without having to account for policing intensity being affected by temperature. Or account for perhaps the much more difficult to address how temperature affects criminal behaviour observe-ability. Or account for the difficult to measure preponderance of an officer to report all observed infractions, and avoid assuming the officer's body is not affected by similar temperature-induced psychological or physiological mechanisms theorized to be affecting criminal bodies.

First, Ranson (2014) combines 1980-2009 UCR statistics (Uniform Crime Report) with daily temperature to find that monthly reports of United States county-level rape, aggravated assault, and simple assault increase almost linearly with hotter temperatures. We examine more recent data beginning January 13, 2017 and ending March 11, 2024). An update is of interest as the period of time beyond includes the aftermath of the global financial crisis, the introduction of the first iPhone 3GS, the influence of social media, the geo-political stability of the world, a global pandemic, and scientific consensus on human induced climate change.

Second, Baysan et al. (2019) find that 1990-2010 Mexican drug-trafficking homicides and suicides increase with hotter temperatures (mean temperature $20°C$ ours $12°C$) and that economic factors only partially mitigate the relationship between temperature and crime, arguing that psychological and physiological factors that are affected by temperature play an important role in crime. We speak directly to potential psychological channels exacerbating and potentially alleviating the temperature-gun-violence relationship we study.

Third, Heilmann et al. (2021) find that 2010-2017 Los Angeles neighbourhood-level crimes increase by 1.72% when daily maximum temperature exceeds $23.8°C$. They leverage administrative internal policing data to ensure the crime increase is not due to changes in policing presence on hot days. We circumvent the need for internal policing data by leveraging always-on acoustic microphones that detect criminal behaviour itself, rather than relying on crime *statistics* which are the result of a compound causal chain.[2]

Fourth, Colmer and Doleac (2023) combine 1991-2016 NIBRS with daily temperature to examine whether policies (more prohibitive concealed-carry laws) can attenuate the temperature–homicide relationship. They find the introduction of such policies reduce the temperature-gun-violence relationship by an average of 4%.

As a preview of our results, we find that a $1°C$ warmer day results in approximately a 1.4% increase in gun-violence attributable to temperature. In our setting, the 90th percentile of day-to-day temperature swings is $6°C$ ($8°C$ for cold days). This means that 1-in-10 days

[2]See previous footnote.

could experience 8.4-11.2% more gun-violence from variation in temperature alone. Our main results are resilient to an extensive battery of robustness tests, alternative functional forms, and other research design decisions. We find that the COVID-19 pandemic, a source of great frustration for many, exacerbated the temperature-gun-violence relationship, but that the relationship has since *returned to normal*. We also find an opposing effect; when many in the city are positively dosed with a win of Chicago's most followed team (the NFL's Bears), we find the temperature-gun-violence relationship significantly attenuated.

The remainder of this paper is structured as follows. Section 2 details the data. Section 3 discusses the econometric specifications. Section 4 presents the main results. Section 5 probes psychological channels through which temperature may affect gun-violence. Section 6 contains a collection of robustness tests. Section 7 concludes.

2 Data

2.1 Crime Data

Our source of crime data is taken from acoustic sensors placed throughout the city which are designed to automatically detect and determine the location of outdoor gunfire. The sensors and system were designed by SoundThinking (previously known as ShotSpotter) and the data is publicly available through the Chicago Open Data Portal. The original intention behind implementation of the system was to shorten response times of the Chicago Police Department to potential gun-violence. The system works by alerting a human analyst when at least three sensors detect a potential gunfire sound. If they determine the sound is a gunshot, the analyst alerts the Chicago Police Department to the location of the gunfire. The data begins 2017-01-13 continuing to the present and is provided on an 'incident' basis where an observation can be either a single or multiple gunshots. On average, there are 72.31 incidences of gun-violence on a given day (summary statistics are in Table A1). This average belies the large variation of gun-violence, which we display in Figure 1. In the figure, we have winsorized days with more than 200 incidents (0.62%) for readability. The distribution shows consistent gun-violence, with a long right tail. Notably, there were no shots detected for only 16 of 2594 (0.73%) of days and half of the days in our sample have at least 71 incidences of gun-violence.[3]

2.2 Environmental Data

Our source of weather data is taken from the recordings by the *in situ* weather station at Chicago Midway Airport, which provides daily temperature and precipitation readings with 100% coverage during the study period. Notably, we confirmed there were no changes in hardware during the study period[4] allowing for cleaner between-day and between-period comparisons than in settings where the hardware may have changed. During the sample period, the average daily temperature is 11.64°C, which belies the variation in temperature experienced in the city given its climate of cold winters and hot summers.[5] A histogram of daily temperatures is provided in the right panel of Figure 1. The distribution reveals that experiences of both hot and cold weather are common, where 23.22% of days have an average temperature above 22.2°C and 14.31% of days have an average temperature below freezing. Temperatures vary significantly day-to-day. For example the 90th percentile change between-day is 6.11°C for the study period, which increases when temperatures are cold to 8.06°C.

[3]We exclude from the analysis July 4, December 31, and January 1, as fireworks can be difficult to distinguish from gunshots.

[4]See this page detailing the service records for (GHCND:USW00014819)

[5]Köppen climate classification of Dfa characterized by the coldest month averaging below 0°C and at least one month averaging above 22°C, with no significant precipitation differences between seasons.

3 Methods

We follow the broader temperature-outcome literature in applying a non-parametric 'binned' approach, followed by a more parsimonious linear specification.[6] Specifically, we begin by estimating the following using ordinary least squares:

$$s_d = \alpha + \sum_{k=1}^{8} \beta_k \times Temp_d^k + \mathbf{X}_d + \gamma_y + \delta_m + \eta_{dow} + \varepsilon_d \tag{1}$$

Where s_d represents city-wide shots detected on day d. $Temp_d^k$ is equal to one if temperature on day d is in bin k. $\mathbf{X}_d$ is a series of daily-level weather controls including wind vectors and precipitation. γ_y, δ_m, and η_{dow} are year, month, and day-of-week fixed effects. We then turn to a linear specification both for parsimony and ease of interpretation for interaction terms.[7]

$$s_d = \alpha + \beta_0 \times Temp_d + \mathbf{X}_d + \gamma_y + \delta_m + \eta_{dow} + \varepsilon_d \tag{2}$$

Where all variables are exactly as defined in the non-parametric approach with the exception of $Temp_d$ which represents the average daily temperature on day d.

3.1 Identification

This analysis estimates the impacts of temperature fluctuations within the city on criminal behaviour conditional on other local weather conditions as well as calendar-based factors. The key identification assumption is that unobserved factors associated with criminal behaviour are not correlated with temperature conditional on other local weather conditions or the accounted-for calendar effects. For non-linear estimations, we must make the additional assumption that the relationship between temperature and gun-violence within each 5°C bin is constant. For linear estimations, this assumption is expanded to assume the relationship

[6] See Graff Zivin and Neidell (2014),Barreca et al. (2016),Cook and Heyes (2020),Waldinger (2022) and LoPalo (2023) for examples.

[7] Only after finding an approximately normal relationship, see Cook and Heyes (2020), Waldinger (2022), and Colmer and Doleac (2023) for examples.

between temperature and gun-violence is constant over the temperature support.

4 Results

4.1 Basic Plot

Figure A1 provides a basic plot of temperature and gun-violence, without adjustment by weather and calendar controls. Each marker is sized proportionally to the number of observations in each 5°C wide bin. The plot suggests a positive relationship between average daily temperature and gun-violence, accordingly we have superimposed a line of best fit. Obviously, without accounting for elements such as precipitation or variations by-month, the plot does not offer definitive evidence of a positive association, we find the initial effect size to be substantial and are reassured that the 'raw data' seems to corroborate our later results and their interpretation.

4.2 Non-Linear

Our first set of main results are presented in Figure 2. The regression's dependent variable is the number of city-wide gun-violence incidents on a particular day, while the primary independent variables are a set of indicators. Each indicator takes the value one if the average daily temperature is within the range associated with that temperature bin. In the left panel, we plot the regression coefficients for the 9 evenly-spaced 5°C temperature bin indicator variables explicitly defined in Equation 1. The reference bin consists of days with comfortable temperatures between 15 and 20°C. We have included 95% confidence intervals in the shaded region. The coefficients of this preferred specification are also presented in column 3 of Table A2. Despite the non-parametric specification, once the effects of precipitation, wind, and various calendar controls are accounted for, a remarkably linear pattern emerges.[8] Said differently, the lower the temperature, the less gun-violence occurs. The estimated effects are both large and statistically significant, well beyond the 1% statistical significance threshold. For example, even a one-bin cooler day as compared to the reference category represents a 6.862 reduction in the total count of gun-violence incidences occurring, representing around 10% of the average. In the right panel, we present a reasonable alternative to the perhaps arbitrary division by evenly spaced temperature bins by conducting this exercise instead using temperature deciles. Our reference group necessarily changes to the 10% of observations with comfortable temperatures between 16.11°C to 20.27°C. We are relieved to see that the relationship and its broadly linear characterization continue to hold using another reasonable data division. The coefficients (which are also presented in Table A3) remain large and statistically significant, well beyond the 1% threshold. Following what appears to be a relatively strong linear relationship in the data, we now proceed through the rest of this paper using the more parsimonious linear specification.

4.3 Linear

Our main linear results are presented in Table 1. The dependent variable is once again the number of city-wide gun-violence incidents on a particular day, while the primary independent variables is now the average daily temperature as explicitly defined in Equation 2. The first column represents the sparsest specification which does not include any control variables - that is simply correlating gun-violence and temperature much in the same manner as Figure A1. In the second column we introduce controls for potential effects of the broadly defined 'calendar' by including year fixed effects, month fixed effects, and day-of-week fixed effects. Our preferred specification is presented in the third and rightmost column, where we additionally control for precipitation, and two wind vectors which separately represent the average daily direction and magnitude of the north-south and east-west components.

[8] See Appendix Figure A2 and column 1 of Tables A2 and A3 for the following exercise without these controls. While the temperature-gun-violence relationship is approximately linear below the comfortable temperature range, it is only with controls that the upper temperatures behave in a similar fashion.

In all columns, the estimated effect can be interpreted as follows. For every additional 1°C warmer temperature an additional gun-violence incident occurs in the city. The inclusion of calendar controls in the second column and additional weather controls in the third column does not meaningfully disturb this estimate. Compared against the daily average number of gun-violence incidents in the city, each additional 1°C warmer day represents an increase in gun-violence by 1.4%. While every additional gun-violence incident may be one too many more, we also note that the 90th percentile of day-to-day temperature changes is around 6°C (8°C when cold-only temperatures are considered) suggesting that 1 in 10 days could see a 8.4-11.2% increase in gun-violence *from the increased temperature alone.*

4.4 Leads and Lags

While not our main focus, before turning to some of the mechanisms that may drive the temperature-gun-violence relationship, we examine whether temperature exposure in the days before or after the fact affect gun-violence.

Specifically, we add both temperature leads (average temperature for the day prior, two days prior, three days prior, and so on) for the gun-violence event as well as lags (average temperature for the day after, two days after, three days after, and so on). The inclusion of leads and lags to our specifications accomplishes two things. First, we can attempt to differentiate between a 'stock' of a temperature effect from a 'flow' in terms of the mechanism that drive temperature to influence gun-violence. Second, while the introduction of lags (that is temperatures after the fact) may capture the anticipatory effect of temperature (tomorrow's forecast may indicate it is better to delay my commission of gun-violence), in the absence of that, we might take the presence of large and statistically significant lags to be indicative of misspecification of our model (since there is seemingly no good reason for temperature tomorrow to affect gun-violence today).

We present the results for including the temperature realisations from seven days prior to seven days after the gun-violence incident in Figure A3.[9] We find the results interesting for three reasons.

First, the main result is surprisingly robust to the inclusion of so many controls. The coefficient of the same-day average temperature's magnitude and statistical significance remains relatively unchanged with the inclusion of 1,2,3 all the way up to 7 leads and lags. This suggests that whatever mechanism between temperature and gun-violence is at work, it must be operating on a particularly short time scale.

Second, the estimated coefficients for temperatures leading up to the gun-violence incident are not large nor are they statistically significant. With a variable such as temperature, which exhibits inter-day dependence, it would not have been surprising to find our unstructured OLS coefficients to more-than-occasionally offer statistical significance due to inter-day temperature dependence. That 0 of the 14 extra lead and lag controls (and only 3 of those in the Table's previous columns' 42 coefficients) offer statistical significance nor a large magnitude reassures us that whatever mechanism temperature affects gun-violence is contemporaneous in nature rather than cumulative or anticipatory.

4.5 Heterogeneity

This subsection details some heterogeneity temperature has on the incidence of gun-violence by comparing when it is typically hot versus typically cold in the city. Classified as a 'hot-summer humid continental' climate, the hottest month for Chicago averages above 20°C while the coldest months for the city average below 0°C. In Figure A5, we present 12 box plots to examine the distribution of average temperature by month of the year. The hottest temperatures typically occur in June, July, and August, while the coldest temperatures could be considered January, February, March, November, and December. The remaining months tend to have temperatures in a more comfortable range. This seasonal variation stands in arguably sharp contrast to the seasonal non-variation depicted in Appendix Figure A6 which

[9] We also present the coefficients in Appendix Table A4, where the figure represents the right-most column. In Appendix Figure A4 we graphically present the first through sixth columns as well.

presents similar box plots for the distribution of gun-violence incidences by month. There is little variation in the minimum, inter-quartile range, median, or surprisingly even the maximum observation in any of the months. This combination of seasonal variation in temperature and less variation in gun-violence allows us a rich support to examine heterogeneous effects in temperature on gun-violence.

In the right panel of Figure A5, we present the results of applying the linear specification of Equation 2 (minus the month fixed effects) by month. The estimated effect of temperature on gun-violence varies significantly by month and offers a striking pattern, and one consistent with the non-linear results presented in earlier Figure 2. Bluntly, higher temperatures in the cold and cool months have a large, positive, and statistically significant effect on gun-violence incidence. This is in contrast to the hottest three months of the year, where additional temperature has a near-zero (or even a possibly negative) effect on gun-violence. This exercise suggests that it is not additional heat during hot temperatures that increases gun-violence in temperate areas like Chicago, but instead the loss of cool and cold temperatures. Unfortunately, this may drive more than anticipated increases in gun-violence under the projected rightward-shift of the entire temperature distribution in the city following climate change, if projections of crime increases are focused on hot temperatures alone.

5 Potential Mechanisms

5.1 Frustration - COVID-19

For this analysis, we will consider three periods of time. The 'pre-COVID' period which we will define as ending when the COVID-19 pandemic was declared by the World Health Organization on March 11, 2020. For the sake of convenience, we will define a 'post-COVID' time period as the period after March 11, 2022 (beginning on the second anniversary of the WHO's declaration) until the end of our sample period of March 11, 2024 (the fourth anniversary). The left panel of Figure A7 displays the number of confirmed COVID-19 cases beginning on March 20, 2020. We include a dashed line at the beginning of the presented data (we do not plot the zero cases for the pre-COVID period) and a dashed line when we define the post-COVID period. While this evenly spaced construction may raise eyebrows, we take as significant motivation the the right panel of the figure, which shows that our defined post-COVID period coincides with the end of the last significant wave of deaths attributable to the disease.[10]

In Table 2, we present estimates of the temperature-gun-violence relationship and how it was affected by the pandemic. Column 1 estimates our preferred linear specification on the pre-COVID period. Our model estimates that an additional 1°C warmer day results in an increase of 0.69 more gun-violence incidents, which remains large and statistically significant well beyond conventional thresholds. Column 2 repeats the specification, now restricted to the COVID-19 period. Our estimate of the temperature-gun-violence relationship remains statistically significant and grows meaningfully in magnitude compared to the pre-COVID period. This is consistent with the frustration-aggression hypothesis that the exceptional period defined by the pandemic, in conjunction with less incapacitation from cold weather, would significantly lower the threshold required for some stressor to ultimately result in gun-violence.[11] Column 3 demonstrates robustness of the analysis by including, linearly, controls for the number of cases and deaths attributable to the disease. We note that both the magnitude and statistical significance of the estimate are almost unchanged. Column 4 re-introduces the pre-COVID period in order to directly compare the temperature-gun-violence relationship before the additional frustrations of the pandemic began. The temperature coef-

[10]It would not be until 5 May 2023, that the WHO Emergency Committee on COVID-19 recommended that COVID-19 no longer fit the definition of a Public Health Emergency of International Concern.

[11]In Table A5, we include an interaction term for each of the 5 implemented 'types' of lockdown that the city ordered (school closing, workplace closing, cancelling public events, restrictions on gatherings, and stay-at-home orders) as classified by the Oxford COVID-19 Government Response Tracker. All columns suggest that the period of time defined by these lockdowns led to a high gun-violence-temperature sensitivity. Columns 1-5 individually identify each of the lockdown 'types' but as they tend to be highly correlated (implemented at the same time or a day after another) we also include their minimum in columns 6 (are there any restrictions in place) and the maximum in column 7 (are all restrictions in place). The temperature-gun-violence relationship and its interaction term with these lockdowns are large and statistically significant in all cases.

ficient returns to its approximately pre-COVID magnitude. We also introduce an interaction term of daily temperature with an indicator variable that takes the value one during the COVID-19 period. The estimated coefficient of 0.51 represents a temperature-gun-violence relationship that is statistically significantly (as well as economically) greater than during the pre-period, to the tune of around 75% stronger. Column 5 examines the post-COVID period only, in the same manner as column 2 examines only the COVID-19 period, and similarly finds a large and statistically significant relationship between temperature and gun-violence. Column 6, as in column 3, confirms the robustness of the now post-COVID relationship to the inclusion of controls for the number of COVID-19 cases and deaths. Column 7, which pools the COVID and post-COVID periods, introduces an interaction between temperature and an indicator variable that takes a value one during the post-period. The magnitude of the interaction term can be interpreted as the COVID-19 period was characterized by an exceptionally strong temperature-gun-violence relationship, which reduced significantly in the post-COVID period. To complete our analysis of these three periods, we conduct a final comparison in Column 8 between the pre-COVID and post-COVID periods. This analysis, which drops the period between March 11, 2020 and March 11, 2022 finds that while there remains a large and statistically significant relationship between temperature and gun-violence after the pandemic is 'over,' there is no significant difference between the pre-COVID and post-COVID periods. In other words, the additional frustration and aggression leading to increased temperature sensitivity during the pandemic seems to have returned back to 'normal.'

5.2 Aggression - Football

In Table 3, we examine the role of a *positive* event for the city, in contrast to the previous frustrations represented by COVID-19. Here, we examine when the most-followed Chicago sports team (the Bears) win a regular season game. In column 1, we restrict the sample to game days only. In column 2, we include the day before and the day after game day. In column 3, we include game day, two days prior, and two days after. The column 1 event-study approach (which averages over the 114 'events' during the sample) finds two interesting estimates. First, the estimate of the temperature-gun-violence relationship is large and statistically significant even with the significantly reduced sample window. Second, while an NFL win is associated with the possibility of additional gun-violence in and of itself, the *interaction* between an NFL win and temperature is large, statistically significant, and negative. For example, in column 1, the magnitude of the temperature-gun-violence relationship is 1.42 (which represents the relationship on game day after an NFL loss) when the Bears win, this relationship is significantly attenuated by the negative coefficient to around a third of the loss-day magnitude. This remains true for the game day only specification, and those in columns 2 and 3. In columns 4,5, and 6 we repeat the analysis in the first three columns while redefining the indicator variable to now take a value of one if and only if the NFL win was *expected* (as defined by sports betting odds). This is in order to remove the possibility of NFL losses which are anticipated from diluting any attenuation effects we may estimate in the first three columns. Indeed, we find this is the case - an expected NFL win almost completely negates the temperature-gun-violence relationship *on game day.* When we add additional time on either side of this win, the attenuation remains large but no longer fully counteracts the relationship. We take this analysis, and the COVID-19 presented in an earlier section, as suggestive evidence that the temperature-gun-violence relationship is sensitive to both negative and positive 'stressors.'

6 Robustness

6.1 Behaviours

Our focus in this paper is to examine the temperature-gun-violence relationship. Our hope in our preferred specification is that, controlling for calendar effects such as year, month, and especially day-of-the-week (in addition to the weather controls) there is no omitted variables in the error term which could bias our estimates. It is not *a priori* obvious to us whether population gun-violence should increase with increased time at home versus, for example, time spent at work. To account for how temperature may affect behaviours, which in turn may affect the incidence of gun-violence, we leverage the mobile-phone tracking data provided by Google. Originally released for analysis of the COVID-19 pandemic by tracking population level changes in exposure behaviours (e.g. spending more time at home, versus in retail establishments etc.), this powerful data allows us to control for how behaviours and potential exposure to gun-violence changes with temperature (albeit within an admittedly special period of time - see the COVID-19 frustration section).

In Table A6, we first correlate temperature with behaviour. The dependent variable in column 1 is additional time spent at retail establishments compared to a pre-COVID-19 baseline. The magnitude of the statistically significant temperature coefficient represents 0.36% more time spent in retail establishments for every 1°C warmer day. In column 2, the dependent variable is time spent in grocery stores. Column 3 through 6 represent time in parks, transit, work, and home, respectively. For all away-from-home behaviours there is a positive and statistically significant relationship between temperature and additional time in the behaviour. These stand in contrast to the significantly *reduced* time spent at home with additional temperature. Our next step is to question whether gun-violence is related to these behaviours.

In Table A7, the dependent variable returns to the number of daily gun-violence incidents. In column 1 (which includes the controls we use in our preferred specifications throughout), the primary independent variable is additional time spent in parks. We find that additional time in parks is associated with additional gun-violence. The succeeding columns introduce each of the five other behaviours afforded to us by the mobility data. Two behaviours emerge as significantly affecting the amount of gun-violence - additional time spent in parks increases gun-violence while additional transit time (defined as time spent at places like bus stations) is associated with less gun-violence. While we remain cautious of over-interpreting these controls, our goal is to demonstrate the robustness of the temperature-gun-violence relationship to the inclusion of otherwise surprisingly detailed behavioural data. Table A8 shows our results. As hoped, the coefficient representing the temperature-gun-violence relationship remains large and statistically significant regardless of the inclusion of these behaviour controls.

6.2 Placebos

In this section we describe the results of an exercise we conducted to reassure ourselves that the effect magnitude and statistical significance of our primary results reflect a 'true' underlying effect and are not simply an artifact of our analysis. Our data at a fundamental level is represented by two vectors - the number of gun-violence events that have occurred in the city on a given day paired with that day's temperature. To generate a placebo, we simply break the connection between the number of gun-violence incidents and temperatures by 'shuffling' with replacement. For this exercise, we do not require a shuffled temperature day to be a particular 'distance' from the true day following the statistical non-significance of all leads and lags in Section 4.4. We then use our preferred linear specification (which corresponds to the rightmost column of Table 1) now replacing daily temperature with temperature that was randomly shuffled for the sample period. The resulting t-statistics are presented in Figure A8. Displayed is a histogram of 1,000 t-statistics from 1,000 placebo regressions, each representing a different 'shuffle' of the temperature vector. We have included black dashed lines at the traditional significance thresholds of absolute value 1.96. We are reassured that *less than* 50 of the 1,000 regressions are statistically significant at the 5% level, and further that the mean of the distribution does not seem significantly far from 0. The t-statistic of our main result's preferred specification is 12.63, which lies far to the right of any of the placebo-generated t-statistics. Bars are 0.14 wide, corresponding to exactly 14 bars between 0 and 1.96. There would be 90 bars between 0 and our preferred specification's t-statistic.

6.3 Functional Forms

Our primary dependent variable in this paper is the number of gun-violence incidents per day in the city, which is a non-negative integer-valued count variable. Our primary method of estimation is ordinary least squares, however there are both efficiency gains to be gained and negative predicted values to be shed with a potentially 'more appropriate' model. We begin by using the most popular count model Wooldridge (2010), Poisson regressions estimated via maximum likelihood and presented in Table A9. Reported are the incidence-rate ratios, that is the coefficients can be interpreted as approximately percentage increases. The specifications from the left to right columns exactly match those of our main results in Table 1. We see that regardless of specification, the Poisson model provides a) a positive and statistically significant relationship between temperature and gun-violence incidence and b) the estimated magnitude is consistently 1.4% or almost exactly what we see in our main OLS estimates. While these estimates are reassuring, we take our investigation of functional form one step further in Table A10, where we present estimates based on negative binomial regressions - typically applied when the dispersion of the count data is too much for the Poisson model. Once again we see that regardless of specification, the different functional form provides a) a positive and statistically significant relationship between temperature and gun-violence incidence and b) the estimated magnitude is consistently 1.5% or just above what we see in our main OLS estimates.

6.4 Alternative Temperature Metrics

Our primary independent variable throughout this paper has been the average daily temperature, calculated following much of the temperature-outcome literature by taking the midpoint between the daily maximum and daily minimum reported by the temperature monitor. In Table A11, we demonstrate the robustness of our results to the use of alternative temperature metrics. In column 1, we reproduce our preferred specification for reference. In column 2, we replace average temperature with daily maximum temperature, one of the daily average's components. The magnitude and statistical significance of our estimates remains undisturbed, which we also see in column 3 when we replace maximum with minimum temperature. In column 4, we now use data from different monitoring stations than elsewhere in the paper. Here, we use the average temperature that was hourly recorded by the 9 weather stations along Chicago's beaches (and operated by the city instead). The estimate effects are nearly identical to our preferred specification.

6.5 Outliers

The dispersion of the temperature realizations displayed in the right panel of Figure 1 and the gun-violence distribution in the left panel (which is winsorized) suggest that outliers in either of the two distributions could be driving the magnitude of the main results, their statistical significance, or both. While the non-parametric estimates of, for example, Figure 2 help with this regard, we now turn to an explicit exercise where we winsorize the extremes of both the dependent and primary independent variables. Our results are presented in Table A12. Column 1 estimates our preferred linear specification while winsorizing the 5^{th} percentile of the distribution - that is any of the coldest 5% of days are assigned days that are much less cold. In column 2, we winsorize the hottest 5% of days, while in column 3 we apply both cold and hot winsorization. In both, our results remain reassuringly unchanged. We repeat this exercise in columns 4,5, and 6 where instead we winsorize the dependent variable at the 5^{th} and 95^{th} percentiles, and then both. Once again our results are reassuringly undisturbed.

6.6 Alternative Standard Errors

Throughout the paper, we have used standard errors robust to heteroskedasticity. Despite the important cluster-robust inference literature, it is unclear what level our analysis should be clustered at to allow for within-cluster correlation. Nevertheless, we subject our preferred specification to a battery of alternative standard error formulations and find they make small difference to our estimated effects' statistical significance. The results are presented in

Table A13. In column 1, we reproduce our preferred specification for reference. In column (2) we cluster results by month (3) temperature ventiles (4) gunshot ventiles (5) two-way ventile clustering (6) standard errors are bootstrapped.We are reassured that in none of the reasonable standard error structures we apply does the estimated coefficient's statistical significance fall below conventional thresholds.

7 Conclusion

A number of studies have examined the connection between temperature and criminal statistic production. Our approach is different for two reasons. First, we estimating the large reductions in gun-violence currently being afforded by inclement winters and likely to be lost under climate change. Second, our focus explicitly measures criminal **behaviour** rather than many previous investigations between temperature and crime. Specifically, if our primary outcome variable had instead been a criminal statistic such as from the Uniform Crime Report, local police report, or from the National Incident-Based Reporting System, a causal chain of events must have occurred. Criminal behaviour must occur, that crime must be observed, that observation must be reported, that reporting must lead to recording. In our setting, which uses always-on automated microphones listening for the sound of criminal behaviour itself, how temperature may affect each of the steps in the causal chain is removed from our estimates. It is for this reason we may interpret our results as follows. There is a strong and positive relationship between temperature and gun-violence. A 1°C warmer day is associated with an additional gun-violence incident, representing 1.4% of the mean. The 90th percentile change day-to-day represents a change of 6°C (and 8°C when cold). For this reason, 1-in-10 days could have up to 11% more gun-violence from the temperature alone. We find this effect in both linear and non-linear non-parametric specifications. We find that only contemporaneous temperature matters for gun-violence, and that additional temperature increases gun-violence significantly in the cold and cool months of the year in contrast to the hottest months. We identify the potential mechanism of frustration-aggression using both negative (COVID-19) and positive (NFL wins) mood shocks, finding evidence that external events meaningfully adjust the temperature-gun-violence relationship. The effect we identify is demonstrably robust, surviving placebos, outliers, alternative measurement, and a battery of standard error calculations.

Our rich data setting allows us to examine the effects of temperature on criminal behaviour, and identify possibly unaccounted for protections currently being afforded by cold temperatures which may be lost in coming decades following climate change. Investigation of whether these effects generalize to the remainder of North America and further could be a fruitful area of future research.

8 Tables

Table 1: Temperature and gun-violence (linear)

	DV: Shots		
	(1)	(2)	(3)
Avg. Daily. Temp. (C)	1.01***	0.98***	1.01***
	(0.07)	(0.08)	(0.08)
Year FE		Y	Y
Month FE		Y	Y
Day-of-week FE		Y	Y
Precipitation			Y
Wind			Y
Observations	2,593	2,593	2,593
$100 \times \frac{\beta}{\overline{shots}}$	1.40	1.35	1.39

Notes: An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. $100 \times \frac{\beta}{\overline{shots}}$ represents the percentage change compared to the mean of the dependent variable the estimated regression coefficient represents. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 2: Temperature and gun-violence (COVID-19 frustration)

	Pre-COVID	COVID-19			Post-COVID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. Daily. Temp. (C)	0.69***	1.13***	1.15***	0.67***	1.65***	1.69***	1.24***	1.03***
	(0.07)	(0.19)	(0.19)	(0.08)	(0.16)	(0.16)	(0.14)	(0.12)
COVID-19=1 × Temp. (C)				0.51***			0.41***	
				(0.09)			(0.12)	
Pre-COVID=1 × Temp. (C)								-0.07
								(0.10)
COVID-19 Cases			Y			Y		
COVID-19 Deaths			Y			Y		
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1143	723	723	1867	725	725	1449	1868

Notes: An observation is a day in Chicago (2017-2024, inclusive). Pre-COVID is defined as observations before March 11, 2020. COVID is defined as observations after March 11, 2020 through March 11, 2022. Post-COVID is defined as observations after March 11, 2022. The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3: Temperature and gun-violence (Reverse-frustration)

	DV: Shots					
	(1)	(2)	(3)	(4)	(5)	(6)
	T	T±1	T±2	T	T±1	T±2
Avg. Daily. Temp. (C)	1.42***	1.51***	1.13***	1.10**	1.55***	1.11***
	(0.48)	(0.29)	(0.22)	(0.47)	(0.30)	(0.21)
NFL Win=1	3.04	7.92**	3.57			
	(5.58)	(3.52)	(2.52)			
NFL Win=1 × Avg. Daily. Temp. (C)	-1.02**	-0.85***	-0.44**			
	(0.44)	(0.26)	(0.19)			
NFL Win (Expected)=1				7.77	14.77***	6.75**
				(5.32)	(4.21)	(3.05)
NFL Win (Expected)=1 × Avg. Daily. Temp. (C)				-1.19**	-1.03***	-0.54***
				(0.47)	(0.30)	(0.20)
Year FE	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y
Observations	114	342	562	114	228	448

Notes: An observation is a day in Chicago (2017-2024, inclusive) around scheduled NFL games. The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. *NFL Win* takes the value one if the Chicago Bears won. *NFL Win (Expected)* takes the value one if the Chicago Bears were expected to win. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

9 Figures

Figure 1: Gun-violence and temperature distributions

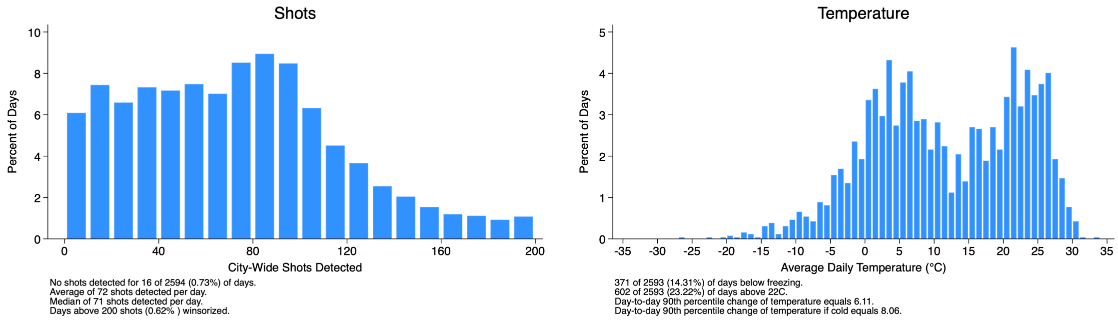
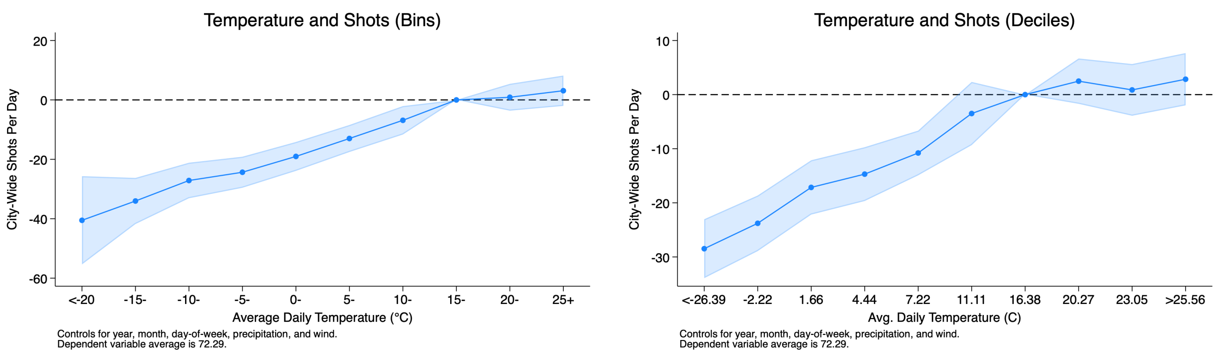


Figure 2: Temperature and gun-violence (Non-linear)



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Appendix Tables

Table A1: Summary statistics

	Mean	Std. Dev.	Min.	Max.
Shots Fired	72.31	45.995	0.00	558.00
Avg. Daily. Temp. (C)	11.64	10.855	-26.39	33.06
Precipitation (Inches)	0.10	0.294	0.00	5.20
Wind Vector (East-West)	0.06	0.453	-2.27	3.98
Wind Vector (North-South)	0.02	0.431	-2.47	3.07
Year	2020.12	2.070	2017.00	2024.00
Observations	2593			

Notes: An observation is a day in Chicago (2017-2024, inclusive).

Table A2: Temperature and gun-violence (Non-linear bins)

	DV: Shots		
	(1)	(2)	(3)
<-20	-48.90***	-38.97***	-40.53***
	(-7.29)	(-5.18)	(-5.35)
-15-	-36.71***	-32.67***	-34.03***
	(-6.53)	(-8.33)	(-8.60)
-10-	-28.58***	-25.90***	-27.13***
	(-6.15)	(-8.60)	(-8.91)
-5-	-28.10***	-23.18***	-24.35***
	(-6.95)	(-8.81)	(-9.15)
0-	-14.62***	-18.12***	-19.03***
	(-3.94)	(-7.37)	(-7.68)
5-	-11.60**	-12.57***	-12.99***
	(-2.99)	(-5.42)	(-5.61)
10-	1.030	-6.543**	-6.862**
	(0.23)	(-2.68)	(-2.82)
15-	0	0	0
	(.)	(.)	(.)
20-	3.058	1.332	0.893
	(0.80)	(0.58)	(0.39)
25+	3.328	3.454	3.097
	(0.81)	(1.33)	(1.19)
Year FE		Y	Y
Month FE		Y	Y
Day-of-week FE		Y	Y
Precipitation			Y
Wind			Y
Observations	2580	2580	2580

Notes: An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is a series of indicator variables corresponding the 5-degrees Celsius 'bin' the average daily temperature is in. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A3: Temperature and gun-violence (Non-linear deciles)

	DV: Shots		
	(1)	(2)	(3)
-26.38889-	-29.23***	-27.02***	-28.48***
	(-7.78)	(-9.76)	(-10.27)
-2.222222-	-22.90***	-22.47***	-23.78***
	(-5.83)	(-8.55)	(-9.09)
1.666667-	-13.01***	-16.10***	-17.15***
	(-3.30)	(-6.29)	(-6.71)
4.444445-	-10.50*	-13.97***	-14.69***
	(-2.54)	(-5.47)	(-5.80)
7.222222-	-6.388	-10.24***	-10.79***
	(-1.55)	(-4.79)	(-5.12)
10.97222-	3.167	-3.090	-3.492
	(0.66)	(-1.03)	(-1.17)
16.11111-	0	0	0
	(.)	(.)	(.)
20.27778-	4.466	3.026	2.490
	(1.06)	(1.40)	(1.17)
23.05556-	4.125	1.272	0.871
	(0.99)	(0.52)	(0.36)
25.55556-	3.910	3.315	2.849
	(0.94)	(1.35)	(1.16)
Year FE		Y	Y
Month FE		Y	Y
Day-of-week FE		Y	Y
Precipitation			Y
Wind			Y
Observations	2593	2593	2593

Notes: An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is a series of indicator variables corresponding the decile 'bin' the average daily temperature is in. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A4: Temperature and gun-violence (Leads and lags)

	DV: Shots						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	±1	±2	±3	±4	±5	±6	±7
Avg. Daily. Temp. (C)	0.97***	0.96***	0.96***	0.98***	0.97***	0.95***	0.95***
	(0.18)	(0.17)	(0.18)	(0.17)	(0.18)	(0.18)	(0.18)
L.Avg. Daily. Temp. (C)	-0.21	-0.00	0.00	0.01	0.00	0.00	-0.03
	(0.13)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
F.Avg. Daily. Temp. (C)	0.24*	0.12	0.13	0.11	0.15	0.19	0.16
	(0.14)	(0.17)	(0.18)	(0.19)	(0.19)	(0.18)	(0.18)
L2.Avg. Daily. Temp. (C)		-0.23*	-0.22	-0.26	-0.24	-0.25	-0.25
		(0.12)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
F2.Avg. Daily. Temp. (C)		0.15	0.14	0.17	0.15	0.11	0.15
		(0.16)	(0.20)	(0.22)	(0.21)	(0.21)	(0.21)
L3.Avg. Daily. Temp. (C)			0.02	0.11	0.06	0.07	0.07
			(0.13)	(0.15)	(0.16)	(0.16)	(0.16)
F3.Avg. Daily. Temp. (C)			0.03	-0.02	-0.04	0.05	0.01
			(0.12)	(0.17)	(0.17)	(0.17)	(0.17)
L4.Avg. Daily. Temp. (C)				-0.07	0.12	0.11	0.11
				(0.15)	(0.16)	(0.18)	(0.18)
F4.Avg. Daily. Temp. (C)				0.06	0.06	-0.04	-0.01
				(0.13)	(0.18)	(0.19)	(0.19)
L5.Avg. Daily. Temp. (C)					-0.23*	-0.17	-0.17
					(0.14)	(0.17)	(0.17)
F5.Avg. Daily. Temp. (C)					0.04	0.30	0.26
					(0.15)	(0.23)	(0.24)
L6.Avg. Daily. Temp. (C)						-0.08	-0.07
						(0.14)	(0.16)
F6.Avg. Daily. Temp. (C)						-0.28*	-0.11
						(0.15)	(0.20)
L7.Avg. Daily. Temp. (C)							0.01
							(0.12)
F7.Avg. Daily. Temp. (C)							-0.18
							(0.12)
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y	Y
Observations	2,561	2,529	2,497	2,465	2,433	2,401	2,369

Notes: An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is the average daily temperature in degrees Celsius. This table includes a series of leads and lags, for example L3 represents 3 day prior average temperature. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A5: Temperature and gun-violence (By lockdown)

	DV: Shots						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	School	Work	Event	Gather	Stay Home	Min	Max
Avg. Daily. Temp. (C)	0.99***	0.93***	0.93***	0.94***	0.92***	0.99***	0.92***
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Lockdown=1 × Avg. Daily. Temp. (C)	0.32**	0.70***	0.75***	0.68***	0.79***	0.96***	0.59***
	(0.12)	(0.13)	(0.10)	(0.12)	(0.12)	(0.25)	(0.10)
Precipitation	Y	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y	Y
Observations	2593	2593	2593	2593	2593	2593	2593

Notes: An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is the average daily temperature in degrees Celsius. The secondary independent variable *Lockdown* takes a value of one if the City had a lockdown of that particular type in effect that day. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A6: Behaviours change with temperature

	DV: Google					
	(1)	(2)	(3)	(4)	(5)	(6)
	Retail	Grocery	Park	Transit	Work	Home
Avg. Daily. Temp. (C)	0.36***	0.20***	2.51***	0.37***	0.13*	-0.14***
	(0.07)	(0.06)	(0.18)	(0.07)	(0.07)	(0.03)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y
Observations	967	967	967	967	967	967

Notes: An observation is a day in Chicago (2020-2022, inclusive). The primary independent variable is the average daily temperature in degrees Celsius. The dependent variables represent the 6 categories of activity available in the Google Mobility Reports. Standard errors robust to heteroskedasticity in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A7: Gun-violence changes with behaviours

	DV: Shots					
	(1)	(2)	(3)	(4)	(5)	(6)
Park	0.17***	0.29***	0.29***	0.29***	0.29***	0.29***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Transit		-0.62***	-0.52**	-0.54***	-0.53***	-0.54***
		(0.07)	(0.21)	(0.20)	(0.19)	(0.18)
Retail			-0.13	0.03	0.04	0.03
			(0.27)	(0.21)	(0.25)	(0.29)
Grocery				-0.27	-0.27	-0.27
				(0.25)	(0.25)	(0.24)
Work					-0.00	-0.02
					(0.20)	(0.27)
Home						-0.08
						(0.87)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y
Observations	967	967	967	967	967	967

Notes: An observation is a day in Chicago (2020-2022, inclusive). The primary independent variables are the 6 categories of activity available in the Google Mobility Reports. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A8: Temperature and gun-violence (Accounting for behaviour)

	DV: Shots						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. Daily. Temp. (C)	1.03***	0.76***	0.67***	0.66***	0.67***	0.67***	0.67***
	(0.17)	(0.18)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Park		0.11**	0.23***	0.24***	0.24***	0.24***	0.24***
		(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Transit			-0.60***	-0.52**	-0.54***	-0.54***	-0.54***
			(0.07)	(0.21)	(0.20)	(0.19)	(0.18)
Retail				-0.10	0.07	0.06	0.07
				(0.27)	(0.21)	(0.25)	(0.29)
Grocery					-0.29	-0.28	-0.28
					(0.25)	(0.25)	(0.24)
Work						0.02	0.03
						(0.20)	(0.27)
Home							0.08
							(0.87)
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y	Y
Observations	967	967	967	967	967	967	967

Notes: An observation is a day in Chicago (2020-2022, inclusive). The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A9: Poisson

	DV: Shots		
	(1)	(2)	(3)
Shots Fired			
Avg. Daily. Temp. (C)	0.0142***	0.0144***	0.0146***
	(0.0010)	(0.0011)	(0.0011)
Year FE		Y	Y
Month FE		Y	Y
Day-of-week FE		Y	Y
Precipitation			Y
Wind			Y
Observations	2593	2593	2593

Notes: Poisson regression model. An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A10: Negative binomial

	DV: Shots		
	(1)	(2)	(3)
Shots Fired			
Avg. Daily. Temp. (C)	0.0151***	0.0157***	0.0161***
	(0.0011)	(0.0012)	(0.0012)
Year FE		Y	Y
Month FE		Y	Y
Day-of-week FE		Y	Y
Precipitation			Y
Wind			Y
Observations	2593	2593	2593

Notes: Negative binomial regression model. An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A11: Alternative temperature measures

	DV: Shots			
	(1)	(2)	(3)	(4)
	Avg.	Max.	Min.	Alt.
Temperature Variable	1.01***	0.91***	0.87***	1.09***
	(0.08)	(0.07)	(0.09)	(0.09)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y
Wind	Y	Y	Y	Y
Observations	2,593	2,593	2,593	2,594
Avg. Temp.	11.64	16.12	7.16	10.99
$100 \times \frac{\beta}{\overline{shots}}$	1.39	1.26	1.21	1.51

Notes: An observation is a day in Chicago (2017-2024, inclusive). The primary independent variable is (1) the average daily temperature in degrees Celsius (2) maximum (3) minimum, and (4) average daily temperature from an alternative suite of monitors. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A12: Winsorization

	DV: Shots					
	(1)	(2)	(3)	(4)	(5)	(6)
	T[5,100]	T[0,95]	T[5,95]	S[5,100]	S[0,95]	S[5,95]
Temperature Variable	1.06***	1.05***	1.11***	1.01***	0.97***	0.98***
	(0.09)	(0.08)	(0.09)	(0.08)	(0.07)	(0.07)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y
Observations	2,593	2,593	2,593	2,593	2,593	2,593
Avg. Temp.	11.88	11.57	11.81	11.64	11.64	11.64
Avg. Shots	72.31	72.31	72.31	72.54	71.05	71.27

Notes: An observation is a day in Chicago (2017-2024, inclusive). The first column winsorizes the lowest 5% of temperatures. The fourth column winsorizes the lowest 5% of daily shots. The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. Standard errors robust to heteroskedasticity in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A13: Alternative standard errors

	DV: Shots					
	(1)	(2)	(3)	(4)	(5)	(6)
	Preferred	Month	Temp. Ventiles	Shot. Ventiles	Both	Bootstrap
Avg. Daily. Temp. (C)	1.01***	1.01***	1.01***	1.01***	1.01***	1.01***
	(0.08)	(0.14)	(0.10)	(0.13)	(0.17)	(0.07)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y
Observations	2,593	2,593	2,593	2,593	2,593	2,593
$100 \times \frac{\beta}{\overline{shots}}$	1.39	1.39	1.39	1.39	1.39	1.39

Notes: An observation is a day in Chicago (2017-2024, inclusive). Column titles represent the level of standard error clustering. The primary independent variable is the average daily temperature in degrees Celsius. The dependent variable is the total number of gun-violence events detected by ShotSpotter. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figures

Figure A1: Temperature and gun-violence (No controls)

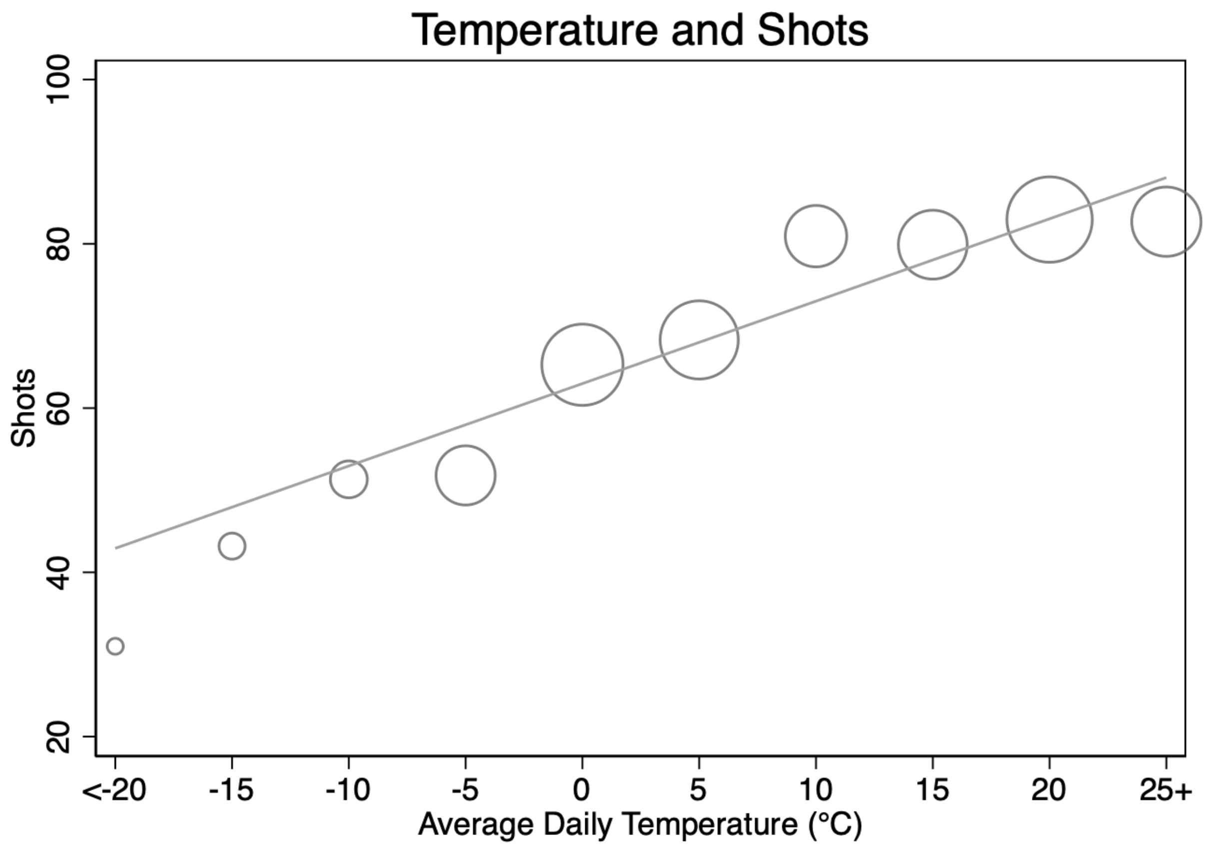

Figure A2: Temperature and gun-violence (Non-linear, No controls)

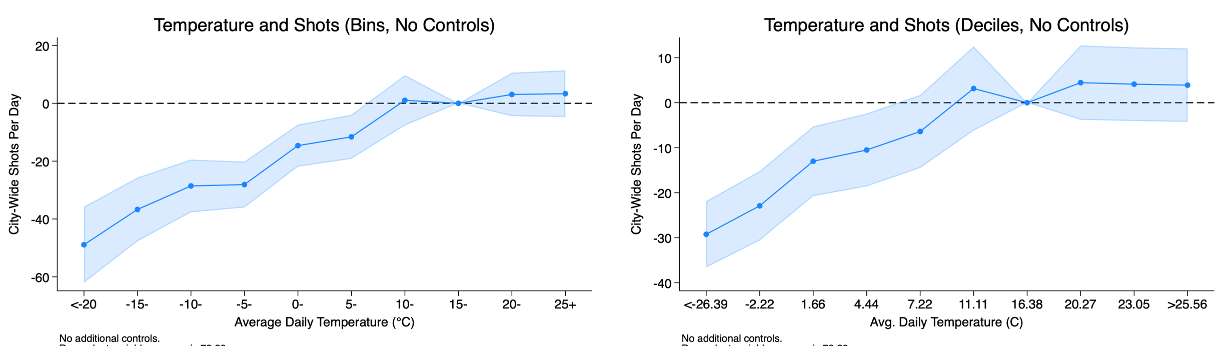

Figure A3: Leads and Lags

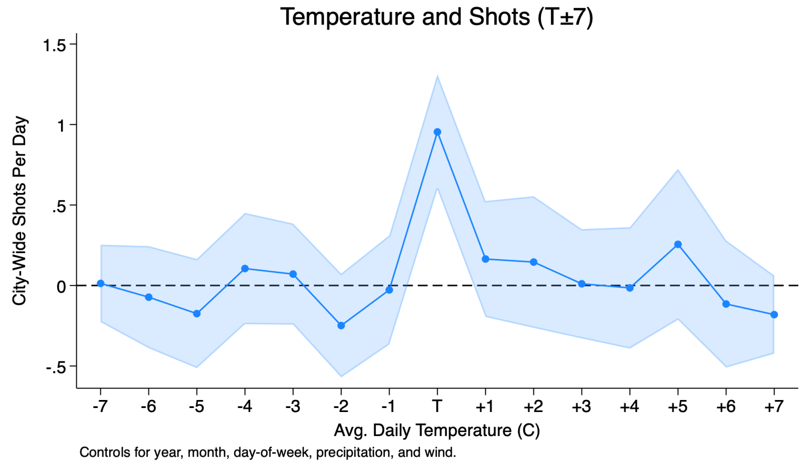

Figure A4: Leads and lags (1-6)

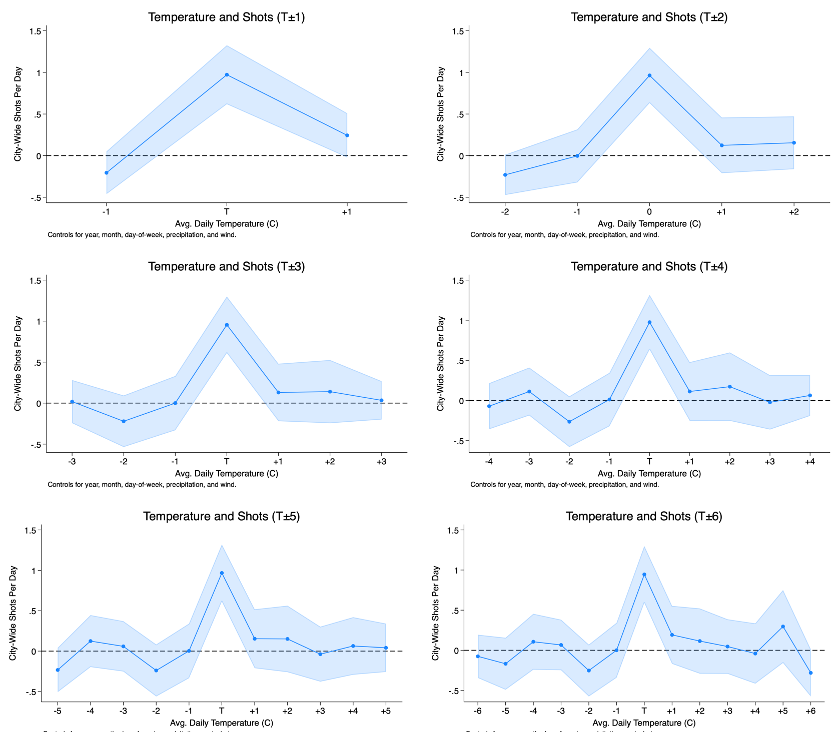

Figure A5: Monthly heterogeneity in temperature and estimated gun-violence relationship

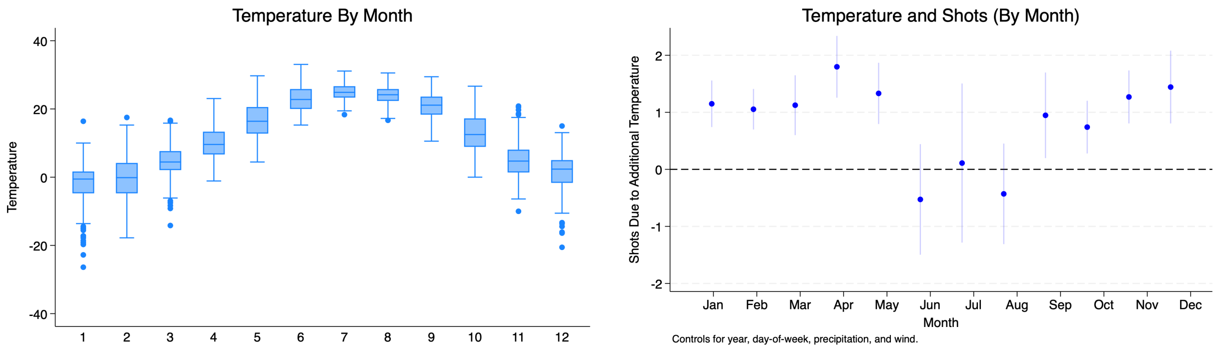

Figure A6: Gun-violence distribution by month

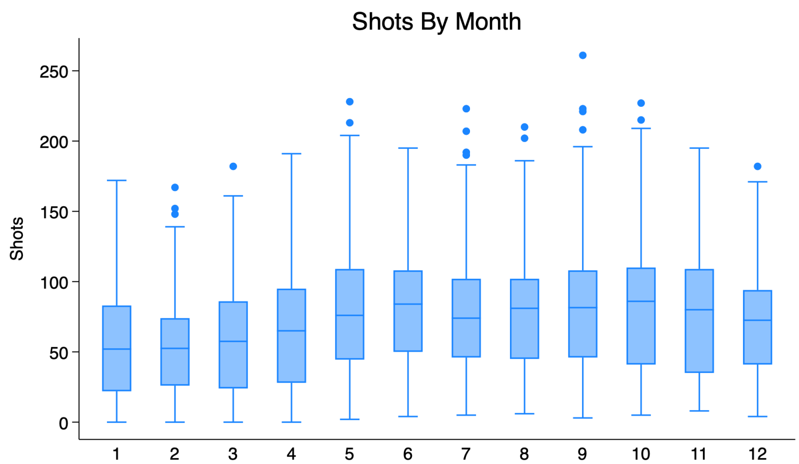

Figure A7: COVID-19 Cases and deaths

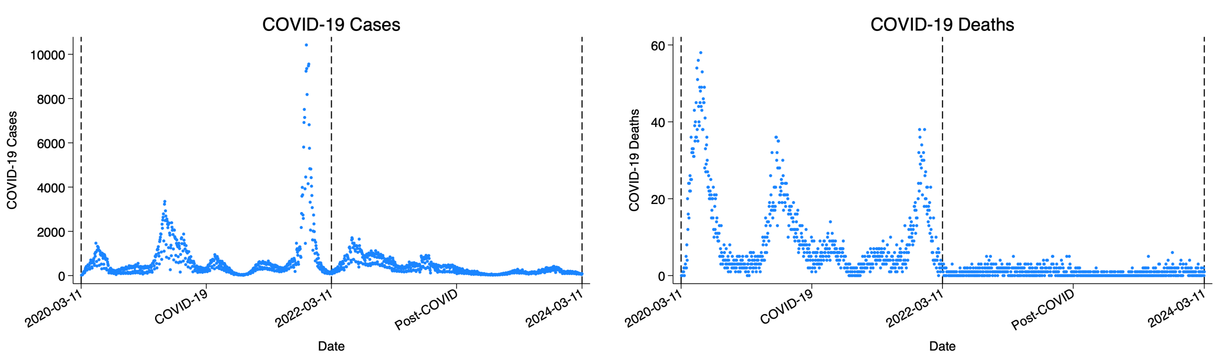

Figure A8: Placebos