Supplementary Information and Analysis

Below we describe our data sources, variables created from these data, the process of data set assembly, and data aggregation process. Additionally, we touch on our control variables and supplementary modeling strategies. Data and complete model results may be found in the accompanying online files (which includes Stata data file, log file and ado file).

A. Data Assembly Process

(1) Uniform Crime Reports (UCR), 1960-2013
Source: Federal Bureau of Investigation

Although annual UCR crime data are generally available online, monthly data, especially those for smaller agencies, are not. Fortunately, the FBI provides raw data files for each year beginning with 1960. We wrote a script in SPSS to unpack those raw data files. Data were subsequently combined in an overall data set and placed in a SPSS file with a time-series cross-section structure that was organized by month, year, and police department. Our initial crime data included about 10.5 million observations (agency * month-year).

Our analyses focus on the aggregate crime categories only: homicide, rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft (see Table 1). Many of the subcategories of offending (such as 'robbery with firearm') are not consistently reported and therefore should not be used in an aggregate study. Homicides (composed of both murder and manslaughter) could not be counted in a reliable or methodologically consistent manner prior to 1974. Reporting only murders would introduce an upward biased trend in the data, therefore the results for homicides are restricted to those after 1974.

Once we assembled the raw data, we examined the file for errors and inconsistencies. Agencies that only reported quarterly, annually, or partial data (leading to blanks in the interim months), were eliminated from the data using embedded data flags. We also manually examined the consistency of the data to find unusual spikes in the data, which would indicate structural – unflagged- problems in reporting. This resulted in the additional exclusions from the data file:

Kentucky: 1987 through 1988; and 1990 through 1992 deleted; New York state: 2002-2012 quarterly reporting was detected and deleted; Minnesota: Deleted in its entirety due to quarterly reporting; Rhode Island: 2000-2006 deleted; Tennessee: deleted 1960, 1983 and 1984; Vermont: deleted 1993-2003; Alaska: deleted 1988-1995; Hawaii: deleted 1989 and 2013; Alabama: 1990-2013 deleted; Colorado: 1996-2007 deleted; Delaware: 1993-1995 deleted; Washington DC: 1993-1997 deleted; Florida 1988-1989 and 1996-2013 deleted; Illinois: 1984-1985 deleted; Kansas 1993-2000 and 2000-2013 deleted.

Combined the previous two steps reduced our initial data with about 4 million cases to almost 6.5 million.

Next, we geocoded the agencies using the reported zip codes (postal code) of the mailing address of law enforcement agencies (headquarters mailing address) in ArcGIS 10.3.1. This step allowed us to merge this data with climate data. This step results in losing nearly 500,000 cases because some agencies did not provide complete return address data on their forms.

Subsequently we aggregated all crime by state, and weighted temperature data by population of each contributing agencies in each state. Each individual state was examined for reporting inconsistencies, resulting in further data exclusions.

Some states have sizeable gaps in their crime data, most notably Florida. In some cases entire years had to be removed because data were either missing entirely or because reporting appeared to have been done quarterly, or annually. We do not believe excluding such years from our analysis has introduced substantial bias to our results. While there is some geographic shift in the total observations over time (most in the Midwest and West, fewer in the South) our sample size is substantial enough to buffer against such shifts, and additionally our models control for within- month and year effects.

Relatively few researchers have worked with raw monthly UCR data because the files are not particularly user friendly (Maltz & Weiss, 2006). In relation to climate change, only Ranson (2014) has used this data source to perform a county-level analysis. Nonetheless, we believe it is a valuable data source that allow us to perform a monthly analysis while generalizing our results.

(2) Climatological data

Source: Global Historical Climatology Network (GHCN), NOAA. Version 3.3.0.2015-12-23 (see ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/v3/)

We collected average monthly temperature data from the GHCN (Lawrimore et al., 2011). Quality controlled mean monthly temperature observations from GHCN data are pre-adjusted for numerous biases and have well known advantages. To create the most consistent temperature reporting for each UCR agency, we only selected stations that reported full coverage for the UCR data period (1960-2013). This allows us to mitigate any further losses of cases during the merger of the two databases. Weather station data includes spatial X and Y coordinates. Using ArcGIS 10.3.1, we merged weather station data to law enforcement agencies. The average distance of the nearest weather station to our agencies is approximately .33 degrees (roughly 20 miles). However, these distances are typically shorter for larger agencies located in urban areas with numerous weather stations, which may slightly bias our results.

In sum, data from 1,087 weather stations were combined with data from 18,297 law enforcement agencies over a period of over 648 months. Our initial agency level sample with quality checked UCR and climate data covers almost 66% of the US population and between 64% and 70% (depending on the crime type) of total annual reported crimes. The close connection between population and crime coverage suggests we are not oversampling urban communities.

Table A1. Descriptive Statistics

Variable	Mean	Standard Deviation
Homicide	25.02	.23
Rape	101.02	.82
Robbery	610.31	7.35
Aggravated Assault	929.03	8.73
Burglary	3237.62	27.63
Larceny	8171.24	62.11
Temperature Anomaly	-.02	1.75
Days in Month	30.44	.81
Weekends	8.7	.8
Holidays	.83	.69
Elevation	393.57	457.59
# Agencies Reporting	182.70	181.54
Distance to WBAN	.33	.18
Population	3390055	3833908
Unemployment Rate	6.11	1.66
Consumer Price Index	112.79	66.30
Housing Starts	85.93	29.33

(3) Data aggregation

We wanted to retain the richness of the agency-level data to the fullest extent possible during the aggregation process. Therefore, we weighted the climatic data by agency population prior to aggregation. The resulting variable was summed by state in the aggregation process and subsequently divided by the summed population for the state to reconstitute a weighted climatic variable. Doing so allows us to effectively measure our climatic indicators by population density, rather than by simple geographic density. In prior state and international level studies researchers selected temperature data from the largest city in the state (Rotton & Cohn, 2003; Mares & Moffett, 2016). While this approach may be sufficient we intended to ensure as close of a measure as possible. A more recent study uses gridded temperature data (Ranson, 2014), but we felt that direct station data would be a slightly better match with police agencies and better capture micro-level monthly temperature fluctuations.

Although we preferred to have presented an analysis at the agency level, this proved problematic. Not only were some of our panels (agencies) severely unbalanced as a result of gaps in the data, data overflow problems crashed modeling attempts in both STATA and R. Given the overdispersed dependent variables (crime counts), we attempted numerous iterations of negative binomial fixed-effects regression at the agency level. None of the desired combinations of variables would run consistently for all of our dependent variables. Relatedly, numerous agencies report zero counts for one or multiple offense categories. This means that the software unjustifiably disregards them in the analysis. This move likely produces an undesirable, upward bias in our results.

To overcome modeling and estimation problems, we aggregated the data at the state level (for completeness see Table A16). Although one recent study conducted a similar analysis at the county level, such aggregation does not sufficiently fix our issues (Ranson, 2014). Further, police agencies sometimes cover multiple counties. Consequently, some studies advise against using county crime data (Maltz & Targonsky, 2002; Maltz & Weiss, 2006). Others have used the state level as their unit of analysis, although prior attempts have only used annual data

(Anderson, Bushman, & Groom, 1997; Rotton & Cohn, 2003). Given that our aim is to examine the month-dependent relationship between climate change and crime, annual data would be insufficient for our purposes.

To ensure the most detailed aggregation, we aggregated the temperature data as follows. Temperature data were weighted by agency population (Temperature x population) prior to aggregation. The resulting variable was summed by state in the aggregation process and subsequently divided by the summed population for that metropolitan area to reconstitute a weighted temperature variable. This ensured that smaller agencies within a metropolitan area do not equally influence the overall state temperature indicators. Doing so allows us to effectively measure the state temperature by population density. In prior state level studies researchers selected temperature data from the largest city in the state (Rotton & Cohn, 2003) While this approach may be sufficient using the metropolitan level of aggregation, we wanted to ensure as close of a measure as possible to capture microclimatic variation within states.

It is difficult to say how representative our aggregated data are for crime in the US, since our data only are reported offenses. Nonetheless as Figure 2 in the main article shows, the sample's crime rates track reported nationwide annual UCR levels quite well. This suggests our data are likely a good representation of crime in the US.

(4) Control variables

We used numerous controls at various stages of our analysis. In all our models, we include a series of temporal controls that have been used in prior research dealing with seasonal effects. We calculated the number of days for each month, the number of federal holidays for each month, and the number of weekend days for each month. From the weather data, we created two additional controls: distance from the weather station in degrees, and altitude in feet. Both of these are important at the agency and state level of analysis to adjust for agencies with gaps in recording of crime or climate data. For this reason, we also included a count variable for the number of agencies reporting complete data for each state.

In alternative specifications, we included several economic measures: unemployment rate (seasonally unadjusted), consumer price index (seasonally unadjusted) and housing sales. These economic measures were collected from the Federal Reserve (https://fred.stlouisfed.org/), and are measured monthly at the national level. These results are reported in the Stata output, and did not appreciably change our results. These results were excluded from the models that we reported in the paper, as prior studies point out that including additional variables may obfuscate the relationship between crime and climate change. Many economic and social indicators may themselves be impacted by climate change. Generally, very few monthly measures have been measured consistently since the 1960s restricting our choices for socio-economic control factors.

Population data were extracted from the UCR data (population covered by agency) and are reported midyear populations. Because law enforcement agencies do not always coincide with municipal and county boundaries we could not use other population sources such as census data.

B. Measuring climate change effects

Once the data were aggregated at the state level, we used the average temperature variable to calculate two variables that were used in the analysis. In annual data, using raw annual temperatures is fine to model the effects of climate changes as modeling techniques will examine the difference from Year 1 to Year 2. Since our data are specifically designed to examine predictions at the monthly level and have repeating seasonal changes, using raw annual temperatures is not the best approach as part of the difference between Month 1 and Month 2 is not independent, but rather the outcome of normal seasonal temperature variation. Prior research indicates that seasonal temperature fluctuations have a predictable effect on crime (McDowall & Curtiss, 2015). Our current approach mirrors Mares' (2013b) study. We calculated the mean temperature for each month for the entire period and each agency to control for such repeating effects. This variable ('seasonality') captures typical seasonal temperature variations in our analysis. Then, we subtracted this variable ('seasonality') from the original temperature variable to create variable 'Temperature Anomaly.' These temperature anomalies represent the shocks that climate change (unusual temperatures) likely can bring to climate systems. While it would be unfair to say that our variables represent the cumulative effect of climate change (since anomalies in any one month cannot be reliably tied to climate change), it is a proxy climate change measure to examine what happens if temperatures rise above the expected norm.

Since our main goal is to examine the possible influence of climate change on monthly crime levels, we developed a way to examine monthly relationships by creating a series of interactive terms. To compute values for these terms, we multiplied each monthly binary variable by 'temperature anomalies', creating month-specific anomalies (variables January, February, March, etcetera, in Tables 1 and 2 in the manuscript) These interactive variables allow us to separate the specific –by month– associations of unusual temperatures to crime.

For every dependent variable, we ran two model specifications. One base model (non-seasonal) that simply estimates the relation between all monthly anomalies and crime and can be compared to prior studies. A second model (seasonal) that estimates the independent relation of each month's anomalous temperatures to crime.

Another issue we address in our main analysis, is that in fixed effects analysis all units are treated as equally contributing to coefficients, in other words, North Dakota would weight equally as much in the analysis as California; while this in some ways is correct given the unit of analysis we felt that weighing states by their population size (above and beyond internal population change for which we control within the model) would render a more useful estimator for the overall relationship of anomalous temperatures to crime.

C. Control Variables -Results

Aside from our key results, which are reported in the article, here we briefly discuss the results of our control variables from those main models. Our findings hold after the effects of numerous controls, which behave largely as expected and have consistent effects across model specifications within the same crime category. Not surprisingly, longer months typically have higher crime rates than shorter months. The number of holidays in a month is typically negatively related to the number of crimes in a month. The latter is not surprising as the opportunities for some types of larceny (e.g., shoplifting) are reduced due to store closings during holidays (Andresen & Malleson, 2013). The number of weekend days in a month shows a consistent positive relationship with violent crimes but turns negative for property offenses.

Increases in the elevation of a weather station within a state area show a generally negative relationship, suggesting that areas within the same state with a higher elevation have generally lower crime rates. The average distance between the reporting agencies within a state and their closest weather station displays predominantly positive coefficients. Little substantive can be deduced from the latter control factors as there is typically only minimal variance of these factors in a state area. Rather they are important to reduce geographic sampling bias within a state. As expected growth in a state's population is positively associated with a growing number of offenses. Finally, changes in the number of reporting agencies within a state do not significantly alter crime numbers, this suggest no statistical impact from changes in the reporting levels.

D. Robustness Checks

We performed a series of robustness checks to verify the robustness of the findings (see included Stata output file for full results). First, we examined whether our results held with omitted time binaries that act as a proxy for time-varying unobserved confounding variables (see Hainmueller & Hangartner, Forthcoming). This set of time-varying independent variables can include economic indicators such as the consumer price index, unemployment, and housing data. The results are robust across all model specification, as the relationship still holds between temperature anomalies and crime.

Second, we examined whether our results hold because of the modeling technique that we used. We varied the modeling technique by using an OLS regression and a Poisson model, but the results remain unchanged. Similarly, we selectively binned our data into five different groups (depending on climate, population size, and several other variations), and the results did not change.

Third, we varied the functional form and timespan of our model to verify whether the results that we have obtained are the result of the way in which the model is specified, or the timeframe that we use. We vary the functional form of the model by removing one control variable at a time. When we do so, the results remain unchanged. Further, we omit one year at a time, one state at a time, and one month at a time. In all cases, the signs and significance patterns of the results that we have obtained are substantially similar to those that we report here. Where we do observe differences, there is no systematic pattern that suggests that one independent variable, one year, one month, or one state drives the results that we have obtained. Thus, we are confident that the results that we report are not an outcome of random chance.

E. Supplementary Analyses

In addition to our main analysis presented here we examined our results from many additional angles. For all our supplementary comparison models (Tables A2-A15) we only present the key variables that are comparable across models and exclude variables that are on different scales (e.g., population) are not measurable in some cases (e.g., distance to weather station). We also do not report log likelihoods as the models have different sample sizes and thus the log likelihoods provide no solid interpretation for the efficiencies of respective models.

First, we attempted to examine the data at the agency level. However, given the large number of agencies and observations we were unable to successfully run models with all parameters for all dependent variables as the computational power required exceeded the capacity of our software to handle the data in some cases. We could run models for homicides, robberies, aggravated assaults and motor vehicles thefts, and the results are virtually identical to our state level analysis (see Tables A2-A8). Results for this analysis must be considered with substantial caution as law enforcement agencies (~municipalities) with zero observations are dropped from the analysis, likely inflating coefficients somewhat. Additionally, we are not able to run all control variables for these analyses consistently, and panels are more unbalanced. Finally, we were unable to weigh the panels by population, meaning that panels (agencies) with a large population (e.g., New York City) are counted equally in the estimation as panels with a very small population. The latter in particular is problematic as most law enforcement agencies in the US cover relatively small populations. Results for these analyses show slightly higher coefficients than the state level model, but the results are largely consistent with state level analyses, for the average anomaly. There are some divergences when examining the monthly anomaly coefficients (i.january, i.february, etc.), we suspect that the lack of panel balance and lack of population weighing is most likely the contributor as both state and metropolitan coefficients show a lot more consistency.

Second, we examined data in metropolitan/urban areas (*n*=112, see Table A17 for completeness) in which the reporting population exceeds 250K on average. These models were specified with the same controls as our state level analysis, and results reiterate our findings for both average anomaly and month-specific coefficients (the latter not shown, but available upon request). In fact, the coefficients for metropolitan areas (MSAs) are generally slightly larger, which we suspect is an outcome of the distinct geographic and urban bias in the data. Further, given the greater number of gaps in metropolitan data we hold slightly less confidence in this type of analysis.

Finally, we ran "national" models in which we aggregated our raw base crime data to the national level and employ US average anomaly data from NOAA (not weighted by population). Not surprisingly do the latter results show smaller coefficients for our anomaly variables, but the results even to our surprise remain consistently positive and statistically significant, despite the smaller sample size and the reduction in resolution of temperature data. Our national level analysis suggests that while data resolution and sample size may be relevant in obtaining the most accurate prediction, aggregated data may be sufficient to detect general patterns. This would be good news for researchers seeking to replicate our work in different locations across the world.

In addition to exploring our findings at multiple levels of analysis we also explored the results with additional economic control variables (consumer price index, houses sold (in 100K per month) and unemployment rate). These results are displayed in Tables A9-A15. Models (1) and (3) are the standard state-level models reported in the main manuscript; Models (2) and (4) are the models with added economic controls. We added the variables as both raw (not shown) and as first-differenced controls ("D.cpi"; "D.unemploymentrate" and "D.houses sold" in models (2) and (4). to our initial models. We believe the models with the differenced variables to be more appropriate as they exclude seasonality, but the differences between both types of modeling techniques are marginal. The differences between the models with and without economic controls are minimal as well. Both the average anomaly coefficients and the monthly coefficients show only minor variations and our conclusions would not have changed with the inclusion of economic indicators.

We encourage replication of our results and urge researchers interested in our data and models to contact us via e-mail. While we included most datasets here, we are unable to do so for the agency data file as its size is exceptionally large.

Tables A2- A8 Temperature Anomaly Comparison Models

A2 Homicides	(1) Agency	(2) State	(3) Metro	(4) National
Anomaly	1.0088**	1.0072**	1.0096**	1.0038**
	(0.001123)	(0.001868)	(0.001933)	(0.001192)
# Holidays	0.9351+	0.9269	0.8912**	1.0024
	(0.03656)	(0.04678)	(0.03946)	(0.002928)
# Weekend days	1.0086**	1.0060*	1.0069*	0.9984
	(0.002381)	(0.002991)	(0.003071)	(0.002790)
#Days in month	1.0253	1.0444*	1.0530*	1.0025
	(0.01657)	(0.01860)	(0.02372)	(0.002647)
Observations	3,641,886	22,387	46,275	480

A3 Rapes	(1) Agency	(2) State	(3) Metro	(4) National
Anomaly	n/a	1.0153**	1.0158**	1.0092**
		(0.001617)	(0.002131)	(0.001055)
# Holidays		1.0189	0.9596	1.0029
		(0.04409)	(0.03209)	(0.002649)
# Weekend days		1.0029+	1.0037*	1.0045+
		(0.001687)	(0.001767)	(0.002494)
#Days in month		1.0524**	1.0611**	1.0037+
		(0.01268)	(0.01313)	(0.002248)
Observations	n/a	30,623	60,597	648

A4 Robberies	(1) Agency	(2) State	(3) Metro	(4) National
Anomaly	1.0054**	1.0056**	1.0064**	1.0028*
	(4.124e-04)	(0.001527)	(0.001608)	(0.001219)
# Holidays	0.9087**	0.9549*	0.9783	1.0029
	(0.01320)	(0.02145)	(0.01994)	(0.003063)
# Weekend days	1.0009	1.0009	1.0004	1.0016
	(8.700e-04)	(0.001226)	(0.001112)	(0.003009)
#Days in month	1.0194**	1.0197+	1.0197*	0.9969
	(0.005881)	(0.01150)	(0.008834)	(0.003227)
Observations	5,177,895	30,623	60,956	648

A5 Aggravated Assaults	(1) Agency	(2) State	(3) Metro	(4) National
Anomaly	1.0102**	1.0142**	1.0158**	1.0070**
	(3.397e-04)	(0.001628)	(0.001785)	(8.332e-04)
# Holidays	0.9881	0.9603*	0.9532**	1.0048*
	(0.01393)	(0.01538)	(0.01455)	(0.002102)
# Weekend days	1.0089**	1.0102**	1.0095**	1.0057**
	(7.209e-04)	(0.001302)	(0.001166)	(0.001773)
#Days in month	1.0248**	1.0289**	1.0309**	1.0010
	(0.004955)	(0.01045)	(0.007608)	(0.001862)
Observations	5,433,079	30,623	60,704	648

A6 Burglaries	(1) Agency	(2) State	(3) Metro	(4) National
Anomaly	n/a	1.0073**	1.0074**	1.0049**
		(0.001479)	(0.001465)	(0.001002)
# Holidays		0.9244**	0.9346**	1.0029
		(0.01726)	(0.01401)	(0.002393)
# Weekend days		0.9933**	0.9922**	0.9995
		(7.500e-04)	(6.439e-04)	(0.002243)
#Days in month		1.0382**	1.0374**	0.9966
Anomaly		(0.008158)	(0.006676)	(0.002213)
Observations	n/a	30,623	60,956	648

A7 Larcenies	(1) Agency	(2) State	(3) Metro	(4) National
Anomaly	n/a	1.0106**	1.0101**	1.0084**
		(0.001567)	(0.001464)	(7.159e-04)
# Holidays		0.9777	1.0033	0.9969+
		(0.01586)	(0.01502)	(0.001787)
# Weekend days		0.9932**	0.9927**	1.0010
		(7.884e-04)	(7.252e-04)	(0.001703)
#Days in month		1.0472**	1.0448**	0.9989
		(0.005045)	(0.004554)	(0.001750)
Observations	n/a	30,623	60,955	648

A8 Motor Vehicle Thefts	(1) Agency	(2) State	(3) Metro	(4) National
Anomaly	1.0071**	1.0059**	1.0046**	1.0052**
	(2.855e-04)	(0.001702)	(0.001579)	(8.067e-04)
# Holidays	0.9489**	0.9719	0.9883	1.0004
	(0.01054)	(0.02438)	(0.02595)	(0.002021)
# Weekend days	1.0016**	0.9996	0.9987	1.0038*
	(6.082e-04)	(0.001209)	(0.001020)	(0.001924)
#Days in month	1.0333**	1.0433**	1.0440**	0.9972
	(0.004285)	(0.009326)	(0.007260)	(0.001921)
Observations	5,413,566	30,623	60,956	648

For Tables A2-A8:
+ p<.1, * p<.05, ** p<.01
Standard errors are reported in parentheses. For models (1), regular standard errors, for models (2) and (3) clustered robust standard errors, and for model (4) robust standard errors.
All coefficients are exponentiated
n/a: not applicable as models could not be estimated

Tables A9 - A15: Additional Economic Controls Models

A9 Homicides	(1)	(2)	(3)	(4)
Anomaly	1.0072** (0.001868)	1.0073** (0.001871)		
i.january			1.0070* (0.003083)	1.0081** (0.003117)
i.february			1.0027 (0.004599)	1.0029 (0.004643)
i.march			1.0031 (0.003827)	1.0030 (0.003790)
i.april			1.0006 (0.005258)	1.0007 (0.005224)
i.may			1.0029 (0.005018)	1.0028 (0.005135)
i.june			1.0250** (0.008254)	1.0255** (0.008294)
i.july			1.0202** (0.007637)	1.0201** (0.007658)
i.august			1.0123 (0.008070)	1.0123 (0.008107)
i.september			1.0129* (0.005580)	1.0129* (0.005538)
i.october			1.0033 (0.005192)	1.0035 (0.005320)
i.november			1.0086 (0.005422)	1.0086 (0.005495)
i.december			1.0095** (0.003153)	1.0086** (0.002921)
# Holidays	0.9269 (0.04678)	0.9301 (0.04647)	0.9271 (0.04457)	0.9291 (0.04448)
# Weekend days	1.0060* (0.002991)	1.0055+ (0.003145)	1.0059+ (0.003025)	1.0054+ (0.003130)
# Days in month	1.0444* (0.01860)	1.0449* (0.01870)	1.0488** (0.01919)	1.0494** (0.01934)
D.unemploymentrate		1.0035 (0.009623)		1.0067 (0.009844)
D.cpi		1.0031 (0.004852)		1.0040 (0.004978)
D.houses sold		0.9999 (2.799e-04)		0.9999 (2.886e-04)
Log-Likelihood	-102683.3486	-102575.4756	-102682.505	-102574.6352
Observations	22,387	22,364	22,387	22,364

A10 Rapes	(1)	(2)	(3)	(4)
Anomaly	1.0153** (0.001617)	1.0149** (0.001649)		
i.january			1.0182** (0.002945)	1.0181** (0.003193)
i.february			1.0201** (0.003593)	1.0200** (0.003573)
i.march			1.0187** (0.004163)	1.0175** (0.004265)
i.april			0.9991 (0.006165)	0.9981 (0.006135)
i.may			1.0052 (0.003685)	1.0049 (0.003670)
i.june			1.0097 (0.008793)	1.0109 (0.008984)
i.july			1.0001 (0.007338)	1.0004 (0.007352)
i.august			1.0125+ (0.007277)	1.0123+ (0.007261)
i.september			1.0225** (0.005138)	1.0214** (0.005203)
i.october			1.0227** (0.008228)	1.0226** (0.008117)
i.november			1.0119** (0.003778)	1.0127** (0.003754)
i.december			1.0178** (0.003972)	1.0173** (0.003750)
# Holidays	1.0189 (0.04409)	1.0209 (0.04463)	1.0180 (0.04644)	1.0205 (0.04742)
# Weekend days	1.0029+ (0.001687)	1.0025 (0.001671)	1.0033* (0.001628)	1.0027+ (0.001602)
# Days in month	1.0524** (0.01268)	1.0514** (0.01318)	1.0496** (0.01269)	1.0491** (0.01311)
D.unemploymentrate		1.0035 (0.004483)		1.0054 (0.005203)
D.cpi		1.0289** (0.002760)		1.0285** (0.002818)
D.houses sold		1.0000 (1.756e-04)		0.9999 (1.939e-04)
Log Likelihood	-174442.5548	-174041.7705	-174440.7857	-174040.0619
Observations	30,623	30,538	30,623	30,538

A11 Robberies	(1)	(2)	(3)	(4)
Anomaly	1.0056** (0.001527)	1.0060** (0.001533)		
i.january			1.0018 (0.003158)	1.0035 (0.002914)
i.february			1.0086* (0.004351)	1.0086* (0.004359)
i.march			1.0004 (0.002955)	1.0012 (0.003035)
i.april			1.0047 (0.005254)	1.0056 (0.005189)
i.may			1.0025 (0.003635)	1.0017 (0.003590)
i.june			1.0139+ (0.007217)	1.0174* (0.007467)
i.july			1.0146+ (0.007844)	1.0121 (0.007932)
i.august			1.0133 (0.009064)	1.0129 (0.009074)
i.september			1.0122* (0.005675)	1.0127* (0.005711)
i.october			1.0072 (0.005345)	1.0076 (0.005451)
i.november			1.0037 (0.004293)	1.0032 (0.004280)
i.december			1.0065** (0.002541)	1.0055* (0.002474)
# Holidays	0.9549* (0.02145)	0.9669 (0.02176)	0.9607+ (0.02054)	0.9703 (0.02090)
# Weekend days	1.0009 (0.001226)	1.0007 (0.001124)	1.0009 (0.001178)	1.0009 (0.001047)
# Days in month	1.0197+ (0.01150)	1.0250* (0.01196)	1.0178 (0.01188)	1.0234+ (0.01228)
D.unemploymentrate		1.0383** (0.004086)		1.0396** (0.004545)
D.cpi		0.9947 (0.003345)		0.9953 (0.003334)
D.houses sold		1.0000 (1.552e-04)		1.0001 (1.687e-04)
Log-Likelihood	-227149.7512	-226598.9004	-227149.0517	-226598.2462
Observations	30,623	30,538	30,623	30,538

A12 Aggravated Assaults	(1)	(2)	(3)	(4)
Anomaly	1.0142**	1.0142**		
	(0.001628)	(0.001637)		
i.january			1.0175**	1.0182**
			(0.002827)	(0.002783)
i.february			1.0136**	1.0137**
			(0.002392)	(0.002367)
i.march			1.0169**	1.0165**
			(0.002699)	(0.002729)
i.april			1.0158**	1.0154**
			(0.004061)	(0.003970)
i.may			1.0133**	1.0131**
			(0.003088)	(0.003007)
i.june			1.0176**	1.0186**
			(0.006145)	(0.006227)
i.july			1.0057	1.0058
			(0.007116)	(0.007109)
i.august			1.0145**	1.0143**
			(0.004429)	(0.004464)
i.september			1.0243**	1.0239**
			(0.004749)	(0.004759)
i.october			1.0092*	1.0095*
			(0.003941)	(0.004013)
i.november			1.0085+	1.0090+
			(0.004972)	(0.005002)
i.december			1.0114**	1.0111**
			(0.002642)	(0.002653)
# Holidays	0.9603*	0.9632*	0.9555**	0.9584**
	(0.01538)	(0.01540)	(0.01499)	(0.01497)
# Weekend days	1.0102**	1.0095**	1.0103**	1.0095**
	(0.001302)	(0.001193)	(0.001250)	(0.001147)
# Days in month	1.0289**	1.0293**	1.0301**	1.0310**
	(0.01045)	(0.01121)	(0.01063)	(0.01134)
D.unemploymentrate		1.0047		1.0073*
		(0.003232)		(0.003539)
D.cpi		1.0172**		1.0158**
		(0.001839)		(0.001803)
D.houses sold		0.9997**		0.9996**
		(1.107e-04)		(1.168e-04)
Log-Likelihood	-240273.8601	-239696.6054	-240273.2397	-239695.988
Observations	30,623	30,538	30,623	30,538

A13 Burglaries	(1)	(2)	(3)	(4)
Anomaly	1.0073** (0.001479)	1.0073** (0.001487)		
i.january			1.0131** (0.002591)	1.0140** (0.002412)
i.february			1.0104** (0.002528)	1.0105** (0.002526)
i.march			1.0029 (0.002261)	1.0039+ (0.002317)
i.april			0.9926* (0.003668)	0.9937+ (0.003700)
i.may			0.9986 (0.002705)	0.9981 (0.002680)
i.june			1.0084+ (0.004872)	1.0110* (0.005033)
i.july			1.0056 (0.004534)	1.0036 (0.004582)
i.august			1.0185** (0.005745)	1.0184** (0.005784)
i.september			1.0087* (0.003471)	1.0093** (0.003548)
i.october			1.0072+ (0.003997)	1.0075+ (0.004103)
i.november			1.0066+ (0.003488)	1.0060+ (0.003462)
i.december			1.0087** (0.002749)	1.0071** (0.002700)
# Holidays	0.9244** (0.01726)	0.9331** (0.01763)	0.9182** (0.01734)	0.9260** (0.01747)
# Weekend days	0.9933** (7.500e-04)	0.9938** (6.905e-04)	0.9937** (7.481e-04)	0.9941** (7.059e-04)
# Days in month	1.0382** (0.008158)	1.0413** (0.008700)	1.0363** (0.008321)	1.0400** (0.008767)
D.unemploymentrate		1.0294** (0.002779)		1.0308** (0.002850)
D.cpi		0.9879** (0.002213)		0.9879** (0.002264)
D.houses sold		1.0004** (8.033e-05)		1.0003** (7.427e-05)
Log-Likelihood	-284981.3412	-284250.2349	-284980.0402	-284248.925
Observations	30,623	30,538	30,623	30,538

A14 Larcenies	(1)	(2)	(3)	(4)
Anomaly	1.0106**	1.0103**		
	(0.001567)	(0.001605)		
i.january			1.0184**	1.0186**
			(0.002221)	(0.002170)
i.february			1.0192**	1.0191**
			(0.002832)	(0.002838)
i.march			1.0115**	1.0113**
			(0.002328)	(0.002352)
i.april			0.9992	0.9993
			(0.004246)	(0.004264)
i.may			0.9993	0.9990
			(0.003304)	(0.003284)
i.june			0.9998	1.0018
			(0.003913)	(0.004000)
i.july			0.9994	0.9985
			(0.003769)	(0.003766)
i.august			1.0053	1.0053
			(0.005705)	(0.005739)
i.september			1.0062+	1.0058+
			(0.003334)	(0.003347)
i.october			1.0070+	1.0068+
			(0.003626)	(0.003659)
i.november			1.0068*	1.0068*
			(0.003096)	(0.003048)
i.december			1.0138**	1.0127**
			(0.002351)	(0.002367)
# Holidays	0.9777	0.9824	0.9675*	0.9722+
	(0.01586)	(0.01593)	(0.01578)	(0.01590)
# Weekend days	0.9932**	0.9942**	0.9934**	0.9941**
	(7.884e-04)	(6.676e-04)	(7.065e-04)	(6.054e-04)
# Days in month	1.0472**	1.0466**	1.0435**	1.0435**
	(0.005045)	(0.005351)	(0.005809)	(0.006193)
D.unemploymentrate		1.0172**		1.0180**
		(0.003365)		(0.003317)
D.cpi		1.0082**		1.0074**
		(0.002242)		(0.002257)
D.houses sold		1.0005**		1.0004**
		(5.777e-05)		(6.273e-05)
Log-Likelihood	-312215.8272	-311418.5158	-312213.8083	-311416.5707
Observations	30,623	30,538	30,623	30,538

A15 Motor Vehicle Thefts	(1)	(2)	(3)	(4)
Anomaly	1.0059**	1.0058**		
	(0.001702)	(0.001744)		
i.january			1.0099**	1.0102**
			(0.002745)	(0.002420)
i.february			1.0118**	1.0116**
			(0.003714)	(0.003745)
i.march			1.0037	1.0032
			(0.002950)	(0.002916)
i.april			0.9963	0.9963
			(0.004377)	(0.004357)
i.may			1.0019	1.0014
			(0.003986)	(0.003937)
i.june			1.0109	1.0132+
			(0.006824)	(0.007029)
i.july			1.0209**	1.0199**
			(0.005937)	(0.005885)
i.august			1.0143*	1.0141*
			(0.006138)	(0.006167)
i.september			1.0003	0.9999
			(0.004822)	(0.004886)
i.october			0.9986	0.9984
			(0.004903)	(0.004980)
i.november			1.0044	1.0046
			(0.003991)	(0.004034)
i.december			1.0025	1.0018
			(0.002559)	(0.002410)
# Holidays	0.9719	0.9770	0.9638	0.9676
	(0.02438)	(0.02499)	(0.02566)	(0.02590)
# Weekend days	0.9996	1.0001	0.9994	0.9999
	(0.001209)	(0.001033)	(0.001170)	(9.971e-04)
# Days in month	1.0433**	1.0447**	1.0407**	1.0420**
	(0.009326)	(0.009666)	(0.009616)	(0.009911)
D.unemploymentrate		1.0224**		1.0214**
		(0.003789)		(0.003897)
D.cpi		1.0121**		1.0123**
		(0.002831)		(0.002772)
D.houses sold		1.0004**		1.0004**
		(1.213e-04)		(1.179e-04)
Log-Likelihood	-258713.2001	-258061.6781	-258711.9072	-258060.3242
Observations	30,623	30,538	30,623	30,538

For all Tables A9-A15:
+ *p*<.1, * *p*<.05, ** *p*<.01
Robust Clustered Standard Errors in parentheses

Table 16. State Level Observations

State abbreviation	Observations	% Observations Complete
AR	648	100.00
AZ	648	100.00
CA	648	100.00
CT	648	100.00
GA	648	100.00
ID	648	100.00
IN	648	100.00
LA	648	100.00
MA	648	100.00
MD	648	100.00
ME	648	100.00
MI	648	100.00
MO	648	100.00
MS	648	100.00
NB	648	100.00
NC	648	100.00
ND	648	100.00
NH	648	100.00
NJ	648	100.00
NM	648	100.00
NV	648	100.00
OH	648	100.00
OK	648	100.00
OR	648	100.00
PA	648	100.00
SD	648	100.00
TX	648	100.00
SC	637	98.30
IA	636	98.15
UT	636	98.15
VA	636	98.15
WA	636	98.15
WI	636	98.15
WV	636	98.15
WY	636	98.15
IL	624	96.30
MT	624	96.30
DE	612	94.44
TN	612	94.44
HI	611	94.29
KY	588	90.74
RI	564	87.04
AK	540	83.33
NY	516	79.63
CO	504	77.78
VT	504	77.78
DC	491	75.77
KS	480	74.07
FL	408	62.96
AL	360	55.56
Total	30,623	100.00

Table 17. Metropolitan areas included

Metro Area	*Observations*	*% Observations Complete*
Fort Lauderdale, FL	284	43.83
Birmingham, AL	326	50.31
Lakeland-Winter Haven, FL	407	62.81
Orlando, FL	407	62.81
Miami, FL	408	62.96
Tampa-St. Petersburg-Clearwater, FL	408	62.96
New Orleans, LA	466	71.91
Denver, CO	479	73.92
Wichita, KS	480	74.07
El Paso, TX	487	75.15
Buffalo-Niagara Falls, NY	491	75.77
Phoenix-Mesa, AZ	497	76.7
Nassau-Suffolk, NY	504	77.78
Syracuse, NY	515	79.48
Albany-Schenectady-Troy, NY	516	79.63
New York, NY	516	79.63
Rochester, NY	516	79.63
Honolulu, HI	530	81.79
Modesto, CA	538	83.02
Knoxville, TN	553	85.34
Providence-Fall River-Warwick, RI-MA	564	87.04
Lexington, KY	574	88.58
Peoria-Pekin, IL	576	88.89
Columbia, SC	589	90.9
San Antonia, TX	590	91.05
Chattanooga, TN-GA	598	92.28
Shreveport-Bossier City, LA	605	93.36
Rockford, IL	609	93.98
Nashville, TN	612	94.44
Tacoma, WA	612	94.44
Tucson, AZ	614	94.75
Memphis, TN-AR-MS	617	95.22
Richmond-Petersburg, VA	617	95.22
Jersey City, NJ	623	96.14
Boise City, ID	624	96.3
Chicago, IL	624	96.3
Flint, MI	624	96.3
Corpus Christi, TX	625	96.45
Allentown-Bethlehem-Easton, PA	626	96.6
Jackson, MS	631	97.38

Dayton-Springfield, OH	632	97.53
Ventura, CA	632	97.53
Oakland, CA	633	97.69
Charleston-North Charleston, SC	634	97.84
Des Moines, IA	636	98.15
Greenville-Spartanburg-Anderson, SC	636	98.15
Kalamazoo-Battle Creek, MI	636	98.15
Madison, WI	636	98.15
Milwaukee-Waukesha, WI	636	98.15
Norfolk-Virginia Beach-Newport News, VA-NC	636	98.15
Salt Lake City-Ogden, UT	636	98.15
Seattle-Bellevue-Everett, WA	636	98.15
Stockton-Lodi, CA	637	98.3
Bergen-Passaic, NJ	638	98.46
Akron, OH	639	98.61
Austin-San Marcos, TX	642	99.07
San Diego, CA	645	99.54
Ann Arbor, MI	646	99.69
Albuquerque, NM	648	100
Atlanta, GA	648	100
Atlantic-Cape May, NJ	648	100
Baltimore, MD	648	100
Boston, MA-NH	648	100
Canton-Massillon, OH	648	100
Charlotte-Gastonia-Rock Hill, NC-SC	648	100
Cincinnati, OH-KY-IN	648	100
Cleveland-Lorain-Elyria, OH	648	100
Columbus, OH	648	100
Dallas, TX	648	100
Davenport-Moline-Rock Island, IA-IL	648	100
Detroit, MI	648	100
Fort Wayne, IN	648	100
Fort Worth-Arlington, TX	648	100
Gary, IN	648	100
Grand Rapids-Muskegon-Holland, MI	648	100
Greensboro-Winston-Salem-High Point, NC	648	100
Harrisburg-Lebanon-Carlisle, PA	648	100
Hartford, CT	648	100
Houston, TX	648	100
Indianapolis, IN	648	100
Kansas City, MO-KS	648	100

Lansing-East Lansing, MI	648	100
Las Vegas, NV-AZ	648	100
Little Rock-North Little Rock, AR	648	100
Los Angeles-Long Beach, CA	648	100
Louisville, KY-IN	648	100
Middlesex-Somerset-Hunterdon, NJ	648	100
Monmouth-Ocean, NJ	648	100
New Haven-Meriden, CT	648	100
Newark, NJ	648	100
Oklahoma City, OK	648	100
Omaha, NE-IA	648	100
Orange County, CA	648	100
Philadelphia, PA-NJ	648	100
Pittsburgh, PA	648	100
Portland-Vancouver, OR-WA	648	100
Raleigh-Durham-Chapel Hill, NC	648	100
Riverside-San Bernardino, CA	648	100
Sacramento, CA	648	100
Saginaw-Bay City-Midland, MI	648	100
Salinas, CA	648	100
San Francisco, CA	648	100
San Jose, CA	648	100
Scranton--Wilkes-Barre-Hazleton, PA	648	100
Springfield, MA	648	100
St. Louis, MO-IL	648	100
Trenton, NJ	648	100
Tulsa, OK	648	100
Vallejo-Fairfield-Napa, CA	648	100
Washington, DC-MD-VA-WV	648	100
Wilmington-Newark, DE-MD	648	100
Youngstown-Warren, OH	648	100

Sources

Anderson, C. A., Bushman, B. J., & Groom, R. W. (1997). Hot years and serious and deadly assault. *Journal of Personality and Social Psychology*, *73*, 1213-1223. doi: 10.1037/0022-3514.73.6.1213

Andresen, M. A., & Malleson, N. (2013). Crime seasonality and its variations across space. *Applied Geography*, *43*, 25-35. doi: 10.1016/j.apgeog.2013.06.007

Hainmueller, J. & Hangartner, D. (Forthcoming). Does direct democracy hurt immigrant minorities? Evidence from naturalization decisions in Switzerland. *American Journal of Political Science.*

Lawrimore, J. H., Menne, M. J., Gleason, B. E., Williams, C. N., Wuertz, D. B., Vose, R. S., & Rennie, J. R. (2011). An overview of the Global Historical Climatology Network monthly mean temperature data set, version 3, *Journal of Geophysical Research*, *116*(D19). doi:10.1029/2011JD016187.

McDowall, D., & Curtis, K. M. (2015). Seasonal variation in homicide and assault across large U.S. cities. *Homicide Studies, 19*, 303-325. doi: 10.1177/1088767914536985

Maltz, M. D., & Weiss, H. W. (2006). Creating a UCR utility. Washington D.C.: National Institute of Justice. https://www.ncjrs.gov/pdffiles1/nij/grants/215341.pdf

Maltz, M. D., & Targonsky, J. (2002). A note on the use of county-level UCR data. *Journal of Quantitative Criminology*, *18*, 297-318. doi: 10.1023/A:1016060020848

Mares, D. (2013). Climate change and levels of violence in socially disadvantaged neighborhood groups. *Journal of Urban Health, 90*, 768-783. doi: 10.1007/s11524-013-9791-1

Mares, D., Moffett, K. (2016). Climate change and interpersonal violence: A global estimate and regional inequities. *Climatic Change*, *135*, 297-310. doi: 10.1007/s10584-015-1566-0

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economic Management*, *67*, 274-302. doi: 10.1016/j.jeem.2013.11.008

Rotton, J., & Cohn, E. G. (2003). Global warming and U.S. crime rates. *Environment and Behavior*, *35*, 802-825. doi: 10.1177/0013916503255565

UCR annual comparison data, downloaded from “UCR data tool”: http://www.bjs.gov/ucrdata/Search/Crime/Crime.cfm