Does heat cause homicides? A meta-analysis

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Abstract

Several studies provide evidence that heat is positively associated with criminal activity. However, the empirical literature does not provide conclusive evidence about the effect of high temperature on homicides. I examine 156 estimates from 20 studies on the relationship between temperature and homicide rates. In particular, in this meta-analysis I study publication bias using linear and nonlinear techniques together with Bayesian model averaging to explain the heterogeneity in the estimates. After correcting estimates from the publication bias, I find no significant effect of temperature on homicide rates. Moreover, monthly data produce larger estimates. Conversely, studies using data from Asia or the OLS estimation method lead to smaller estimates.

1 Introduction

How do weather factors affect interpersonal violence? The answer to this question is crucial not only for the research that examines effects of climate change on human behavior. A body of literature has examined how weather affects peoples' lives: a meta-study by Frangione *et al.* (2022) conclude that higher ambient temperature increases suicide risks, while Bunker *et al.* (2016) and Cruz *et al.* (2020) provide a meta-analysis of the link between temperature and mortality to conclude that heat causes more deaths.

Existing research mostly supports the conclusion that weather has a causal effect on crime, Horrocks & Menclova (2011). However, scholars such as Rotton & Cohn (2003) argue that existing studies mainly use data from Western countries, and that criminal activities such as rape or robbery are impossible to use as an indicator in an international context. In this paper I aim to overcome the issue of *incomparability* of existing studies by undertaking a meta-analysis of temperature effects on homicide rates. According to Mares & Moffett (2016) or del Frate (2010), homicides are the most suitable crime category for international comparison. Following their argumentation, homicide rates seem to be an appropriate crime statistic for a meta-analysis.

Generally, studies concerning weather effects on crime are motivated by the climate change issue. Following Horrocks & Menclova (2011), there are multiple psychological mechanisms through which weather impacts violent crimes. According to a Negative Affect Escape model by Bell (1992), aggression rises with heat because of increases in discomfort and peoples' irritation, but the trend is *inverse U-shaped.* Rotton & Cohn (2000) propose the General Affect model in which higher temperature stimulates aggression and thus violent crimes. The Routine Activity theory by Felson (1987) suggests that pleasant weather conditions increase the likelihood of a victim occurring. For example, in the Routine Activity model, *better* weather increases social interaction among people which increases the likelihood of crime.

Studies concerning temperature effects on homicides have been growing recently, but the results vary. For example, Mares & Moffett (2016) and Baysan *et al.* (2019) find a positive relationship between heat and homicide rates, but Colmer & Doleac (2022) and McDowall *et al.* (2012) argue that this effect is zero. Misak (2022) finds an insignificant and negative link between temperature and murder rates. Stanley (2001) argues that scholars do not regularly publish insignificant results or results with the *wrong* sign, and thus these authors' decisions distort the evidence. The fact that negative estimates are missing may be due to two factors: actual nonexistence of negative effects or publication bias. All of these facts suggest that a comprehensive analysis of existing literature is needed.

In this paper, I conduct a meta analysis of heat effects on homicide rates. Relevant studies (Figure 1) show that the effect varies among studies (see Figure 3) and also due to different study designs (see Table 4).

I collected 156 estimates from 20 studies and 13 variables that describe the circumstances of the primary studies. The most recent study is from 2022, while the oldest is from 2005. Studies cover the period from 1973 to 2020. The mean effect size as reported in the studies is 0.0048, which means that 1°C temperature increase causes homicide rate to increase by 0.0048.

To deal with publication bias, I start with a funnel plot as proposed by Egger *et al.* (1997). To test for asymmetry, I provide linear tests using ordinary least squares, fixed effects model and linear regressions weighted by the standard error, number of estimates reported in the study and total number of citations of the study, respectively. In addition, I provide nonlinear tests for the presence of publication bias.

My findings indicate that the overall reported effect of temperature on homicide rates is driven primarily by publication bias. Although the mean effect from the reported studies indicates that 1°C causes absolute increase in homicide rates by 0.0048, after correcting for publication bias, the effect is either statistically insignificant or negligable. Based on my model-averaging results, I further demonstrate that studies using monthly homicide rate data tend to report larger estimates. Conversely, studies from Asia or those using OLS regressions report smaller estimates.

The remainder of this paper is structured as follows. Section 2 describes how I collect data from primary studies and provides core dataset statistics. Section 3 focuses on publication bias in the literature. Section 4 investigates the heterogeneity using Bayesian model averaging. Section 5 concludes the paper.

2 Data

2.1 Estimates collection

Following general guidelines for undertaking a meta-analysis such as Field & Gillett (2010) or Havránek *et al.* (2020) I did the following search for articles. Firstly, I searched "homicides+OR+murders+OR+crime+AND+temperature+OR+weather" in Google Scholar. I then went through the first 610 studies manually. After that I did a snowball method from the reference lists of relevant articles. This procedure was repeated again on articles published from 2020 onwards to capture newly published articles. Subsequently, I excluded duplicated results. I decided to exclude the study by Wetherley (2014) because it focuses on temperature effects on homicide rates during extreme weather conditions (typhoons in Philippines), which is not comparable with other studies. I carried out the whole procedure in December 2022 which is displayed in Figure 1. Table 1 provides a list of all studies.

11 studies (55%) analyze short term variation between temperature and homicides using daily data. The remaining 7 studies (35%) and 2 studies (10%) focus on the long-term relationship between heat and murder rates on monthly and annual crime-weather data, respectively. 18 studies (90%) focus on within-country regional variation; only 2 studies (10%) examine cross-country variation among a number of countries. All these differences among studies are later discussed in Section 3.

There are several ways to measure temperature effect on homicides. The majority of articles report a standard level-level regression[1] coefficient from the following equation:

$$HR_i = \beta_0 + \beta_1 \cdot temp + \beta_i \cdot X_i \ ,$$

where *HR* stands for homicide rate per 100,000 people, *temp* is a temperature variable and X_i is a vector of the set of variables controlling for possible heterogeneity.

Michel *et al.* (2016), Trujillo & Howley (2021) and Koppel *et al.* (2022) quantify the effect using and Incidence rate ratio that has the following form:

$IRR = 1 + \frac{\widehat{HR}_{change}}{HR_{base}}$, where $\widehat{HR}_{change}$ is the observed change in homicide

[1] I did not collect log-level, level-log or log-log regressions because I am unable to recalculate these coefficients into level-level form.

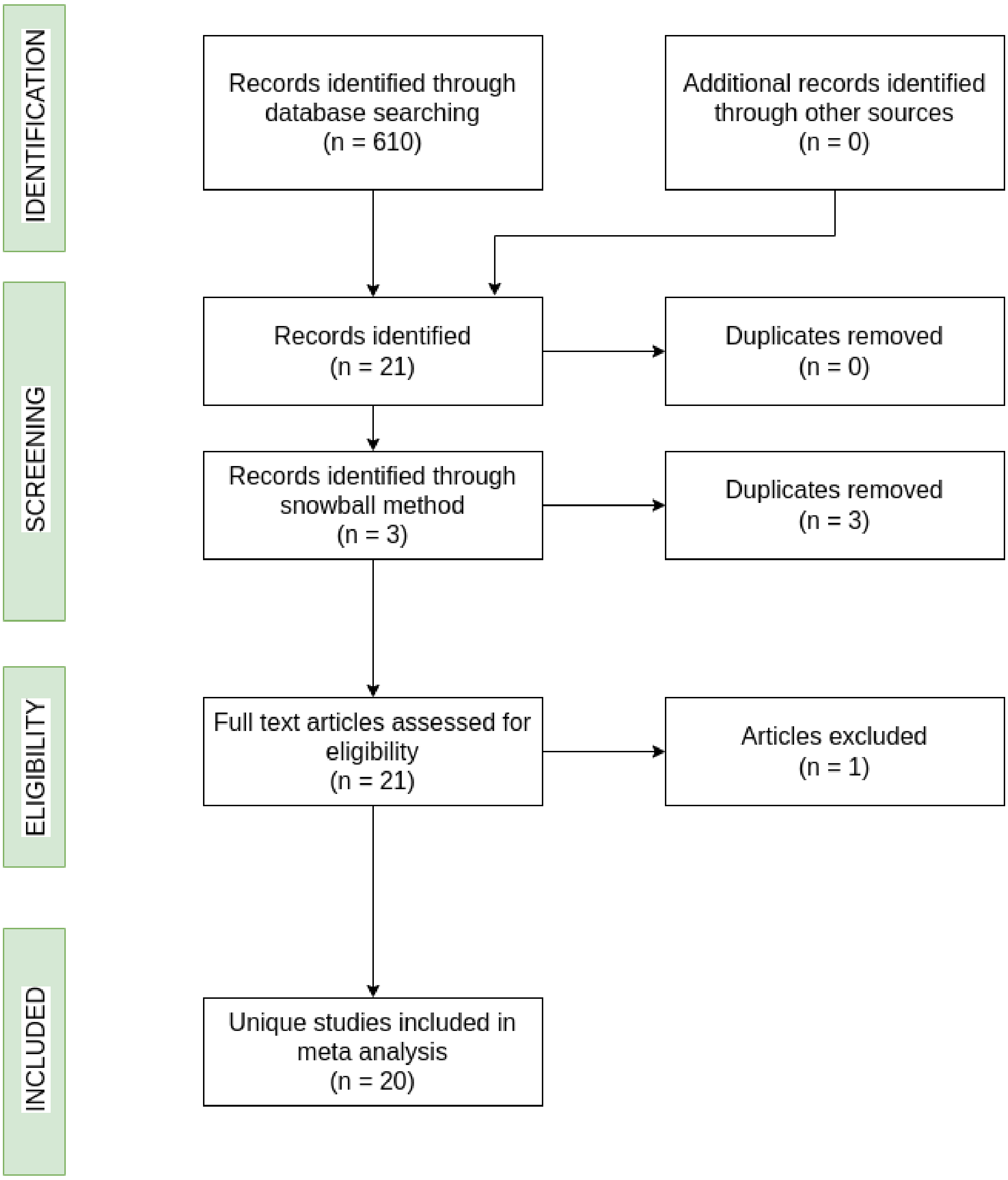

Figure 1: PRISMA flow diagram.

rate caused by 1°C temperature increase and HR_{base} is the baseline homicide rate in the study.

I decided to use regression coefficient to quantify the effect of temperature on homicides. From the interpretation of the regression coefficient above, I obtain that $\beta_1 = \widehat{HR}_{change}$. Fortunately, studies also provided information on the baseline homicide rate HR_{base}, which enables me to calculate comparable β from IRR.

I recalculated the temperature effect to the degree of Celsius. The formula for conversion between Fahrenheit and Celsius degrees has the following form: $Celsius = \frac{Fahrenheit-32}{1.8}$. Because adding constant (in our case 32) does not affect β , I can convert effects in Fahrenheit to Celsius by dividing them by 1.8.

At the end of the data collection procedure, I have 156 estimates from 20 studies.

2.2 Dataset statistics

The mean effect among all studies, as described in Table 4 and Figure 2, is 0.0048 with variance 0.003. In other words, based on simple averaging of collected estimates, a one-degree Celsius temperature increase is associated with a 0.0048 increase in the total number of homicides per 100,000 people.

Figure 3 shows the distribution of effects per each study. The plot suggests that the majority of estimates is positively distributed around zero[2]. The largest estimates are reported in the study by Mares & Moffett (2016), while the lowest effects are reported by Misak (2022). Table 1 provides an overview of the collected studies and their characteristics. I draw several conclusions. Firstly, the lengths of the examined datasets differ among studies. Authors such as Zambrano *et al.* (2022) or Gamble & Hess (2012) analyze homicide rates data from only one year, while McDowall & Curtis (2015) examine data from 1960 to 2004. Secondly, the majority of studies use average temperatures, only a minority use maximum temperatures. Finally, the highest number of estimates used in this meta analysis (86) is from the study by Colmer & Doleac (2022).

[2]Based on tests in Table 6 and Table 7 there is no need for winsorization of the data.

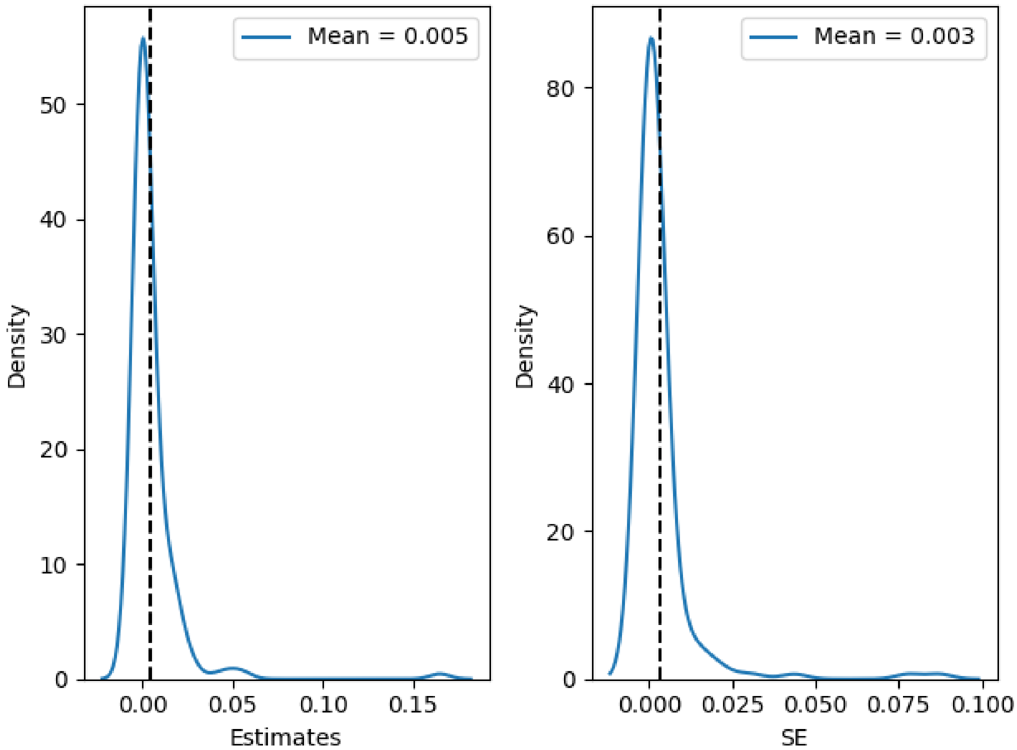

Figure 2: Kernel densities of average temperature estimates and corresponding standard errors
Note: The figure depicts kernel densities for average temperature and number of homicides per 100,000 inhabitants relationship. Estimates on the left, standard errors on the right.

Article	Country	Period	Frequency	Temperature	Estimates	Mean effect	Mean SD
Baysan *et al.* (2019)	Mexico	1990 - 2010	monthly	A	16	0.0174	0.006
Blakeslee *et al.* (2018)	India	2011 - 2016	daily	M	4	0.002	0.044
Colmer & Doleac (2022)	USA	1991 - 2016	daily	A	86	0.0004	0.0002
Ceccato (2005)	Brazil	2001 - 2002	daily	A	2	0.0008	0.0002
Gamble & Hess (2012)	USA	1993 - 1993	daily	A	2	0.0129	0.01
Garg *et al.* (2020)	Mexico	1998 - 2012	daily	A	1	0.0129	0.0038
Heilmann *et al.* (2021)	USA	2010 - 2017	daily	M	1	0.0072	0.006
Koppel *et al.* (2022)	USA	2018 - 2020	daily	A	1	0.000	0.000
Mares & Moffett (2016)	World	1995 - 2012	yearly	A	7	0.0464	0.03
McDowall *et al.* (2012)	USA	1977 - 2000	monthly	A	1	0.0005	0.0003
McDowall & Curtis (2015)	USA	1960 - 2004	monthly	A	1	0.0007	0.0002
Michel *et al.* (2016)	USA	2018 - 2013	monthly	M	1	0.00	0.00
Misak (2022)	Czechia	2005 - 2015	daily	A, M	23	-0.0005	0.001
Schutte *et al.* (2021)	South Africa	20017-2014	daily	A	1	0.02	0.0086
Shen *et al.* (2020)	China	2005 - 2016	daily	A	1	0.0013	0.0012
Simister & Van de Vliert (2005)	World	1977 - 2001	monthly	A	2	0.0069	0.0085
Takahashi (2017)	Japan	2009 - 2015	monthly	A	1	0.001	0.00
Trujillo & Howley (2021)	Colombia	2010 - 2016	daily	M	3	0.00	0.00
Wu *et al.* (2020)	USA	1973 - 2009	monthly	M	1	0.015	0.0107
Zambrano *et al.* (2022)	USA	2019	yearly	A	1	0.0167	0.0779

Table 1: Articles included in the meta-analysis.

A, M stands for average, maximum temperature, respectively.
* Average high temperature for every year.

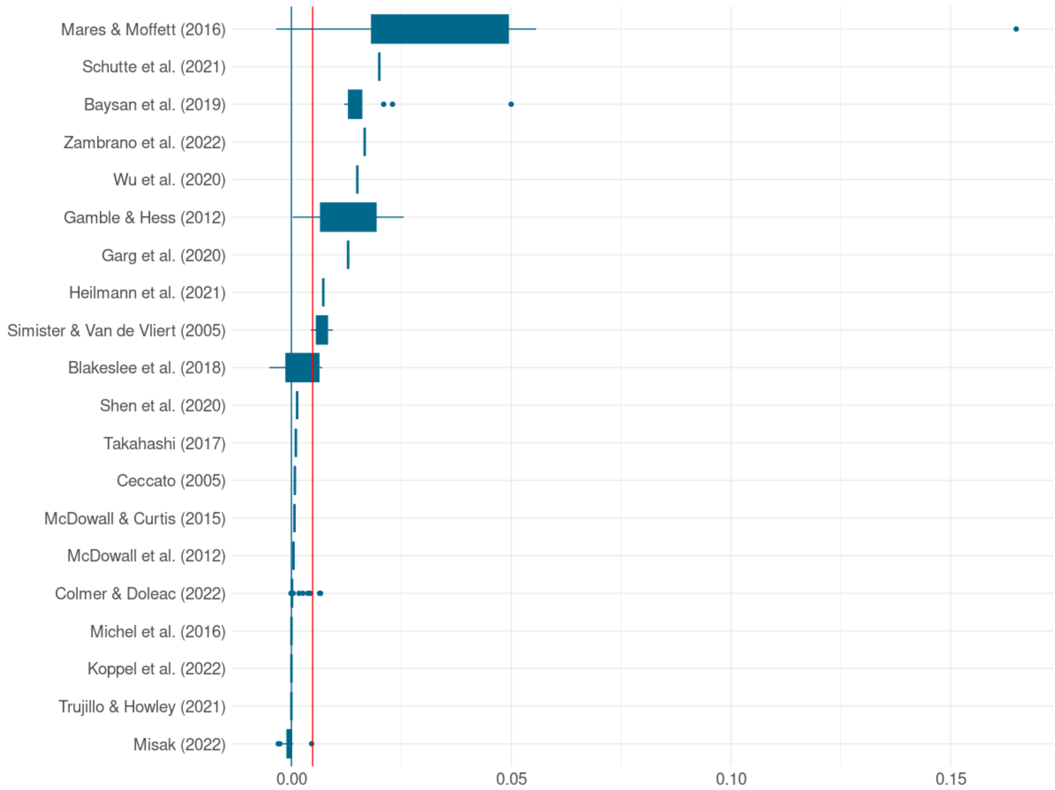

Figure 3: Variation in the estimates across and within studies.
Note: Red line denotes the mean estimate from studies, blue line stands for zero. All 20 studies included.

3 Publication Bias

A standard method for checking the presence of publication bias is a funnel plot. In the case of no publication bias, estimates with higher precision will be plotted close to the average, while the less precise estimates are spread on both sides of the distribution. Any deviation from this shape indicates the presence of a publication bias. The funnel plot in Figure 4 indicates that there is a publication bias among estimates, because its shape seems to be skewed to the right. Nevertheless, the funnel plot is only a simple visual test that we need to further check by linear and nonlinear methods in Table 2 and Table 3.

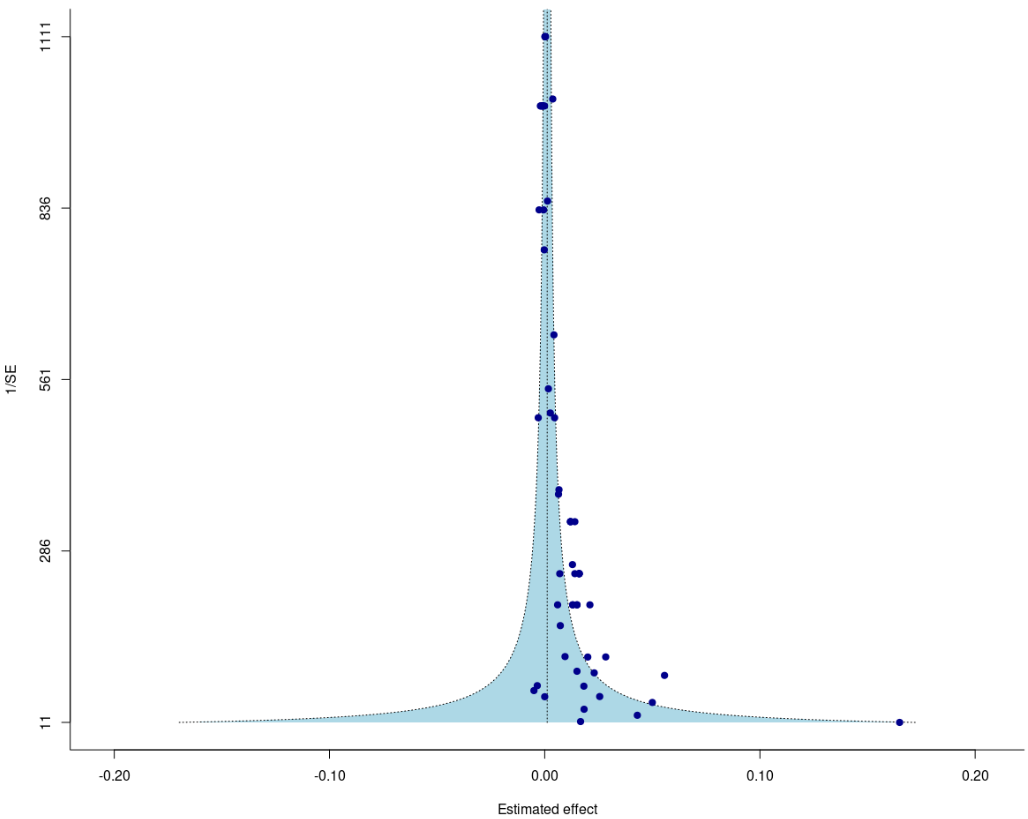

Figure 4: Funnel plots.

Stanley (2005) proposed a formal test for asymmetry in the funnel plot (FAT). The test is based on the following linear regression model:

$$effect_{ij} = \beta_0 + \beta_1 \cdot SE(effect)_{ij} + \epsilon_{ij}$$

Where $effect_{ij}$ stands for i-th estimate of temperature effect on homicide rate with the standard error $SE(effect)_{ij}$ reported in the j-th study. In the case of no publication bias, effects should be independent on their standard errors. In other words, in the absence of publication selection, the *true effect* should be equal to β_0, which we call the *mean beyond bias.* Correspondingly, β_1 stands for the publication bias among collected effects. Table 2 presents the FAT results using various estimation techniques. The first column provides results of the simple OLS regression. FE accounts only for within-study variation. The precision column applies weight proportional to the standard error of each estimate which assigns more weight to more precise studies and therefor directly deals with heteroskedasticity, Stanley & Doucouliagos (2012). The Study column weighs the effect by the number of estimates reported in every study. Citations stands for a regression weighted by the total number of citations of each study. Based on four of five specifications, I argue that there is a significant publication bias among effects. Moreover, none of the linear estimation techniques provides significant results about the mean beyond bias, which indicates that there is no effect of temperature on homicide rates at all and the fact that the mean estimate is positive is due solely to the publication bias.

Table 2: Linear tests for publication bias

	OLS	**FE**	**Precision**	**Study**	**Citations**
SE	1.1303*	2.0025***	1.4808***	0.4782	1.5943***
(Publication bias)	0.5684	0.6591	0.325	0.8345	0.0793
Constant	0.00103	0.0000	0.0000	0.0046	0.0007
(Mean beyond bias)	0.00162	0.0000	0.0000	0.0035	0.0018
Studies	20	20	20	20	20
Observations	156	156	156	156	156

Note: Table provides results for the linear techniques estimating publication bias. Study-clustered standard errors are provided below each coefficient. First row represents the FAT test of publication bias. Second row tests for the mean estimate beyond bias. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

However, linear tests for publication bias yield unbiased estimates of the *Mean beyond bias* if and only if the publication selection is proportional to the standard error, Bajzik (2021). However, in practice, I often do not know

Table 3: Non-linear tests for publication bias

	Stanley *et al.* (2010)	**Furukawa (2019)**	**Vevea & Hedges (1995)**
Mean beyond bias	0.0205***	0.00005	0.0025***
Standard error	(0.0034)	(0.00009)	(0.0009)

Note: This table provides results of our 3 main non-linear techniques for publication bias determination. These tests only provide an estimation of the mean beyond bias. Clustered standard errors are presented in the parenthesis.

the exact form of the publication selection procedure. Therefore, in addition to linear tests for publication bias in Table 2, I employ three non-linear tests as displayed in Table 3. First, the test by Stanley *et al.* (2010) that relies on a statistical trick, namely discarding 90% of the published findings and averaging the most precise 10% of the collected estimates. Second, the test by Furukawa (2019), also known as stem-based method, uses only the most precise estimates and minimizes the mean squared error of the estimates. This non-parametric method tests publication bias under various assumptions. Third, the Vevea & Hedges (1995) test firstly estimates a fixed-effects model where effect sizes are assumed to have a normal distribution. Then, estimate an adjusted model that includes both the original fixed effects model and a series of weights for specific p-value interval, which produces a mean with corresponding standard error adjusted for publication bias. Two of the three tests, namely Stanley *et al.* (2010) and Vevea & Hedges (1995), provide statistically significant results.

To conclude, in the results of linear and nonlinear tests for detecting publication bias, as displayed in Table 2 and Table 3, only two of eight tests provide significant evidence that temperature has a positive effect on homicide rates. The average of all *true effects* from these eight tests is 0.0037, which is 77 % of the 0.0048, which is the average of all estimates. Therefore, I argue that there is either no effect of heat on homicide rates or the effect is smaller than commonly thought.

4 Heterogeneity explained

Existing literature mentions two reasons for systematic differences in the estimates of temperature effects on crime rates. Firstly, according to Ranson (2014): *"annually-averaged data for large geographic units may face challenges with empirical identification of how weather affects crime rates. Furthermore, findings from these studies may be biased by the substantial year-to-year reporting inconsistencies"*.

Secondly, Mares & Moffett (2016) find regional differences in temperature effects on homicide rates. According to their study, there is no such significant effect in former Soviet countries. On the other hand, Mares & Moffett (2016) argue that temperature causes an overall increase in murder rates in North America and Africa. The majority of existing causal heat effects on homicide rates is from the USA (Rotton & Cohn (2003) or Table 1).

Table 4 lists all the codified variables with corresponding mean, variance, and mean and variance weighted by the inverse of the number of observations per study. For the purpose of the meta-analysis I divide the variables into groups describing data characteristics, structural variation, spatial characteristics, estimation techniques and publication characteristics.

Data characteristics. Studies based on annual and monthly data report substantially higher estimates. This conclusion is supported by Ranson (2014) argumentation. Moreover, effects from daily data are the lowest. Finally, mean temperature estimates are higher than maximum temperature estimates.

Structural variation. Scholars such as Rotton & Cohn (2000) suggest that the trend between temperature and crime is curve linear. Based on findings from Table 4, I argue that the $Temperatue^2$ variable makes estimates of the heat effect on homicides negligible or even negative. Similarly, studies that use precipitation as another weather variable seem to produce smaller estimates.

Spatial characteristics. Following Mares & Moffett (2016) and Rotton & Cohn (2003), I divide articles into three geographical clusters based on which countries the data was taken from - USA, Asia and other countries. It seems that studies from Asia and the USA produce substantially smaller estimates than studies from the rest of the world.

Estimation techniques. Table 4 suggests that Poisson regression and OLS estimation techniques produce substantially smaller estimates than other methods.

Publication characteristics. Finally, studies published in peer-reviewed journals suggest that the link between temperature and homicide rates is

	No. of studies	No. of est.	*Unweighted* Mean	Variance	*Weighted* Mean	Variance
Data characteristics						
Annual data	2	8	0.0427	0.0028	1.1458	0.1416
Monthly data	7	23	0.0134	0.0001	0.6419	0.0312
Daily data	11	125	0.0008	0.0	0.2732	0.0074
Mean temperature	15	139	0.0052	0.0003	0.6707	0.0253
Maximum temperature	7	17	0.0014	0.0	-0.0165	0.0005
Structural variation						
Rain variable	14	109	0.0017	0.0	0.4671	0.0152
$Temperature^2$ variable	3	11	0.0005	0.0	-0.1239	0.0007
Spatial characteristics						
USA	9	95	0.0011	0.0	0.3564	0.0091
Asia	3	6	0.0017	0.0	0.0114	0.0003
Other countries	8	55	0.0117	0.0006	0.8186	0.0455
Estimation methods						
OLS regression	8	99	0.0012	0.0	0.4083	0.0087
Poisson regression	3	25	0.0001	0.0	-0.0751	0.001
Fixed effects	5	20	0.0144	0.0001	0.8915	0.003
Other method	4	12	0.0285	0.0022	0.5729	0.11
Publication characteristics						
Reviewed journal	16	45	0.0159	0.0007	0.4312	0.0491
Sample size $>$ 100,000	6	128	0.0021	0.0	1.2001	0.0124
Sample size $<$ 100,000	7	16	0.0253	0.0017	0.5144	0.112
All estimates	20	156	0.0048	0.0002	0.4895	0.0231

Table 4

Summary statistics for different subsets of collected literature. The left-hand part displays unweighted mean effects with corresponding variances. The right-hand part displays means weighted by the inverse number of estimates reported in each article. Detailed explanation of variables is in Table 5.

greater than that reported in non-reviewed articles (such as working papers etc.). Moreover, estimates from a large sample size (more than 100,000 observations) report lower results of the heat-homicides relationship.

4.1 Bayesian model averaging

The goal of this subsection is to analyze which variables, as listed in Table 4, explain the heterogeneity in the estimates reported in the literature. One possible way might be to put all variables into one regression. However, I do not know which of these variables really belong to the *true* underlying model, because I believe that all of them might be important for explaining why the collected estimates vary. Including all variables from Table 4 will decrease the overall precision of the results. Steel (2020) recommends addressing this model uncertainty problem using Bayesian model averaging (BMA).[3] BMA is an application of Bayesian techniques to solve the problem of model selection Fragoso *et al.* (2018). Let K be a set of examining models $M_1, ..., M_K$. Then, using Bayes‘ rule, the posterior inclusive probability (PIP) of model j is:

$$p(M_j|X) = \frac{p(X|M_j) \cdot p(M_j)}{p(X)} = \frac{p(X|M_j) \cdot p(M_j)}{\sum_{k=1}^{K} p(X|M_k) \cdot p(M_k)}$$

I included 11 variables that, according to the discussion in Section 4 above, might have an impact on the estimates reported in the literature. BMA computed 2^{11} possible combinations of regressions that have the following form:

$$HR_{ji} = \gamma_0 + \gamma_1 \cdot SE(HR_{ji}) + \gamma_2 \cdot X_{ji} + \epsilon_{ji}$$

where HR_{ji} stands for j-th homicide rate estimate as reported in i-th study, X_{ji} stands for explanatory variables and SE stands for standard error. Coefficient γ_0 stands for the mean effect corrected for publication bias, while γ_1 denotes the direction of the publication bias, similarly to the linear test for the funnel plot asymmetry discussion in Section 3. The likelihood of each model is represented by the posterior probability and estimated BMA coefficients for each variable are represented by posterior means. Results of the BMA model are provided in Figure 5 and Table 8.

On the vertical axes explanatory variables as described in Table 8 are ranked according to their posterior inclusion probabilities. The horizontal axis shows cumulative posterior model probability. Blue color means the estimated parameter of the corresponding explanatory variable is positive, otherwise the color is red.

[3]BMA is widely used in meta-analysis in economics, e.g. Havranek *et al.* (2015), Havránek *et al.* (2020) or Bajzik *et al.* (2020).

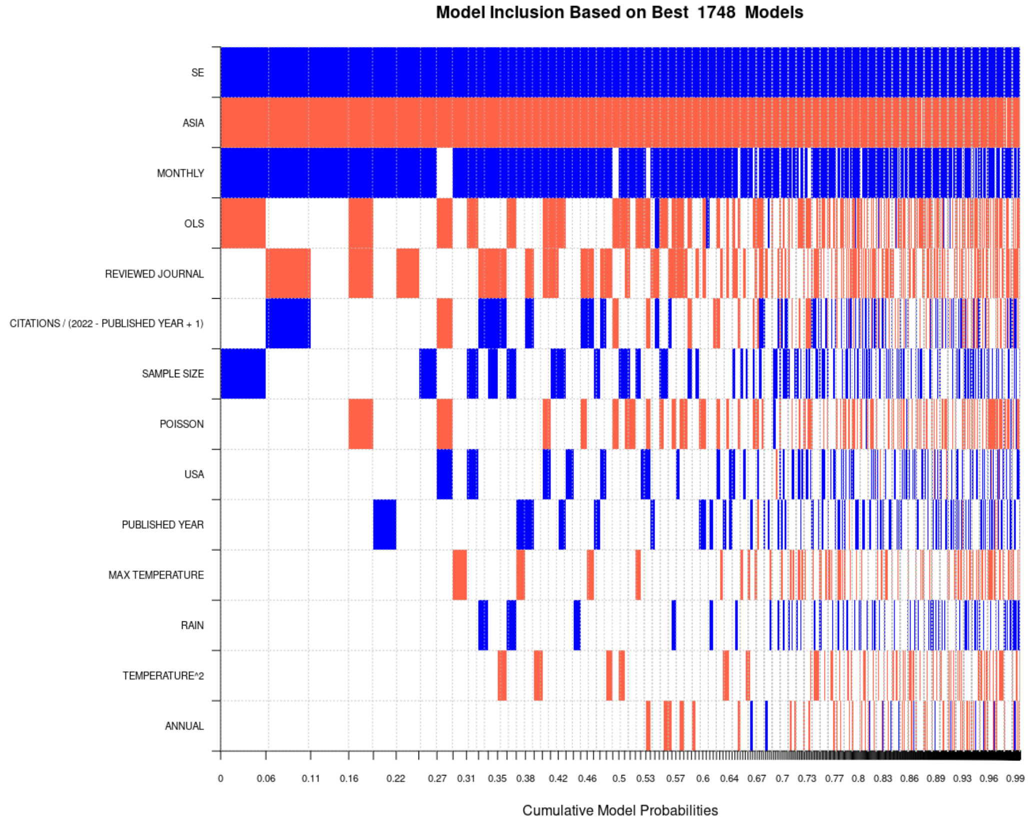

Figure 5: Model inclusion in Bayesian model averaging

The figure displays the results of the benchmark BMA model as reported in Table 8.

Jeffreys (1998) considers posterior inclusive probabilities (PIP) in interval 0.99-1 as decisive, 0.95-0.99 as strong, 0.75-0.95 as positive and 0.5-0.75 as weak. Based on this argumentation, intercept, standard error, dummy variable for Asian countries, monthly data and dummy variable for OLS regression have PIP high enough to provide significant results. Firstly, BMA provides a robustness check that the overall effect of temperature on homicide rates is driven primarily by their standard errors, as discussed in Section 3. Moreover, I argue that studies conducted using monthly data produce higher estimates. This is in line with scholars such as Misak (2022) or Ranson (2014) who mention differences between short-run and long-run temperature effect estimates on crime. Moreover, OLS regression techniques leads to higher estimates compared to other estimation methods such as Poisson regression. This conclusion is also supported by previous evidence, most notably by Horrocks & Menclova (2011) or Ranson (2014). Finally, studies from Asian countries report smaller estimates than studies from the rest of the world. This is in line with the conclusion by Mares & Moffett (2016).

5 Concluding remarks

I present the first meta-analysis of temperature effects on crime rates. Based on my results, the temperature effect on homicide rates, represented by 156 estimates reported in 20 studies, has no significant causal effect. After correcting for publication bias and controlling for 13 aspects of data, such as data characteristics, structural variation, estimation methods, spatial and publication characteristics, it appears that there is no significant effect of temperature on homicide rates or the effect is approximately 23 % smaller than the literature suggests.

Moreover, according to my analyzes of heterogeneity among studies, several additional conclusion can be made. Firstly, studies on monthly data report substantially higher estimates than studies on daily or annual data. Secondly, the OLS estimation technique seems to lead to lower estimated effects of temperature on homicide rates than other methods. Studies from Asian countries also report smaller effects.

After quantitatively examining existing studies, I conclude that higher temperature does not cause an increase in homicide rates.

References

Bajzik, J. (2021): "Trading volume and stock returns: A meta-analysis." *International Review of Financial Analysis* **78**: p. 101923.

Bajzik, J., T. Havranek, Z. Irsova, & J. Schwarz (2020): "Estimating the armington elasticity: The importance of study design and publication bias." *Journal of International Economics* **127**: p. 103383.

Baysan, C., M. Burke, F. González, S. Hsiang, & E. Miguel (2019): "Non-economic factors in violence: Evidence from organized crime, suicides and climate in mexico." *Journal of Economic Behavior & Organization* **168**: pp. 434–452.

Becker, G. S. (1968): "Crime and punishment: An economic approach." In "The economic dimensions of crime," pp. 13–68. Springer.

Bell, P. A. (1992): "In defense of the negative affect escape model of heat and aggression." .

Blakeslee, D., R. Chaurey, R. Fishman, D. Malghan, & S. Malik (2018): "In the heat of the moment: economic and non-economic drivers of the weather-crime relationship." *Working Paper* .

Bunker, A., J. Wildenhain, A. Vandenbergh, N. Henschke, J. Rocklöv, S. Hajat, & R. Sauerborn (2016): "Effects of air temperature on climate-sensitive mortality and morbidity outcomes in the elderly; a systematic review and meta-analysis of epidemiological evidence." *EBioMedicine* **6**: pp. 258–268.

Ceccato, V. (2005): "Homicide in sao paulo, brazil: Assessing spatial-temporal and weather variations." *Journal of Environmental Psychology* **25(3)**: pp. 307–321.

Colmer, J. & J. L. Doleac (2022): "Access to guns in the heat of the moment: More restrictive gun laws mitigate the effect of temperature on violence." *Available at SSRN 4195573* .

Cruz, J., P. C. White, A. Bell, & P. A. Coventry (2020): "Effect of extreme weather events on mental health: a narrative synthesis and meta-analysis for the uk." *International journal of environmental research and public health* **17(22)**: p. 8581.

EGGER, M., G. D. SMITH, M. SCHNEIDER, & C. MINDER (1997): "Bias in meta-analysis detected by a simple, graphical test." *Bmj* **315(7109)**: pp. 629–634.

FELSON, M. (1987): "Routine activities and crime prevention in the developingmetropolis." *Criminology* **25(4)**: pp. 911–932.

FIELD, A. P. & R. GILLETT (2010): "How to do a meta-analysis." *British Journal of Mathematical and Statistical Psychology* **63(3)**: pp. 665–694.

FRAGOSO, T. M., W. BERTOLI, & F. LOUZADA (2018): "Bayesian model averaging: A systematic review and conceptual classification." *International Statistical Review* **86(1)**: pp. 1–28.

FRANGIONE, B., L. A. R. VILLAMIZAR, J. J. LANG, I. COLMAN, E. LAVIGNE, C. PETERS, H. ANISMAN, & P. J. VILLENEUVE (2022): "Short-term changes in meteorological conditions and suicide: A systematic review and meta-analysis." *Environmental research* **207**: p. 112230.

DEL FRATE, A. A. (2010): "–crime and criminal justice statistics challenges." *HEUNI* p. 167.

FURUKAWA, C. (2019): "Publication bias under aggregation frictions: Theory, evidence, and a new correction method." *Evidence, and a New Correction Method (March 29, 2019)* .

GAMBLE, J. L. & J. J. HESS (2012): "Temperature and violent crime in dallas, texas: relationships and implications of climate change." *Western Journal of Emergency Medicine* **13(3)**: p. 239.

GARG, T., G. C. MCCORD, & A. MONTFORT (2020): "Can social protection reduce environmental damages?" .

HAVRANEK, T., Z. IRSOVA, K. JANDA, & D. ZILBERMAN (2015): "Selective reporting and the social cost of carbon." *Energy Economics* **51**: pp. 394–406.

HAVRÁNEK, T., T. STANLEY, H. DOUCOULIAGOS, P. BOM, J. GEYER-KLINGEBERG, I. IWASAKI, W. R. REED, K. ROST, & R. VAN AERT (2020): "Reporting guidelines for meta-analysis in economics." *Journal of Economic Surveys* **34(3)**: pp. 469–475.

HEILMANN, K., M. E. KAHN, & C. K. TANG (2021): "The urban crime and heat gradient in high and low poverty areas." *Journal of Public Economics* **197**: p. 104408.

HORROCKS, J. & A. K. MENCLOVA (2011): "The effects of weather on crime." *New Zealand Economic Papers* **45(3)**: pp. 231–254.

JEFFREYS, H. (1998): *The theory of probability.* OUP Oxford.

KOPPEL, S., J. A. CAPELLAN, & J. SHARP (2022): "Disentangling the impact of covid-19: An interrupted time series analysis of crime in new york city." *American Journal of Criminal Justice* pp. 1–27.

MARES, D. M. & K. W. MOFFETT (2016): "Climate change and interpersonal violence: A "global" estimate and regional inequities." *Climatic change* **135(2)**: pp. 297–310.

MCDOWALL, D. & K. M. CURTIS (2015): "Seasonal variation in homicide and assault across large us cities." *Homicide Studies* **19(4)**: pp. 303–325.

MCDOWALL, D., C. LOFTIN, & M. PATE (2012): "Seasonal cycles in crime, and their variability." *Journal of quantitative criminology* **28(3)**: pp. 389–410.

MICHEL, S. J., H. WANG, S. SELVARAJAH, J. K. CANNER, M. MURRILL, A. CHI, D. T. EFRON, & E. B. SCHNEIDER (2016): "Investigating the relationship between weather and violence in baltimore, maryland, usa." *Injury* **47(1)**: pp. 272–276.

MISAK, V. (2022): "Crime and weather. evidence from the czech republic." *Technical report*, Charles University Prague, Faculty of Social Sciences, Institute of Economic Studies.

RANSON, M. (2014): "Crime, weather, and climate change." *Journal of environmental economics and management* **67(3)**: pp. 274–302.

ROTTON, J. & E. G. COHN (2000): "Violence is a curvir function of temperature in dallas: a replication." *Journal of personality and social psychology* **78(6)**: p. 1074.

ROTTON, J. & E. G. COHN (2003): "Global warming and us crime rates: An application of routine activity theory." *Environment and Behavior* **35(6)**: pp. 802–825.

SCHUTTE, F. H., G. D. BREETZKE, & I. EDLSTEIN (2021): "The relationship between temperature and crime on the cape flats of south africa." *International Journal of Criminal Justice Sciences* **16(1)**: pp. 127–145.

Shen, B., X. Hu, & H. Wu (2020): "Impacts of climate variations on crime rates in beijing, china." *Science of the total environment* **725**: p. 138190.

Simister, J. & E. Van de Vliert (2005): "Is there more violence in very hot weather? tests over time in pakistan, and across countries worldwide." *Pakistan Journal of Meteorology Vol* **2(4)**: pp. 51–66.

Stanley, T. D. (2001): "Wheat from chaff: Meta-analysis as quantitative literature review." *Journal of economic perspectives* **15(3)**: pp. 131–150.

Stanley, T. D. (2005): "Beyond publication bias." *Journal of economic surveys* **19(3)**: pp. 309–345.

Stanley, T. D. & H. Doucouliagos (2012): *Meta-regression analysis in economics and business*. routledge.

Stanley, T. D., S. B. Jarrell, & H. Doucouliagos (2010): "Could it be better to discard 90% of the data? a statistical paradox." *The American Statistician* **64(1)**: pp. 70–77.

Steel, M. F. (2020): "Model averaging and its use in economics." *Journal of Economic Literature* **58(3)**: pp. 644–719.

Takahashi, R. (2017): "Climate, crime, and suicide: Empirical evidence from japan." *Climate Change Economics* **8(01)**: p. 1750003.

Trujillo, J. C. & P. Howley (2021): "The effect of weather on crime in a torrid urban zone." *Environment and Behavior* **53(1)**: pp. 69–90.

Vevea, J. L. & L. V. Hedges (1995): "A general linear model for estimating effect size in the presence of publication bias." *Psychometrika* **60(3)**: pp. 419–435.

Wetherley, E. (2014): "Typhoons and temperature impact crime rates: evidence from the philippines." .

Wu, C. Y., H. F. Lee, & H. Liu (2020): "Effect of temperature and precipitation change on crime in the metropolitan area in virginia, usa." *Asian Geographer* **37(1)**: pp. 17–31.

Zambrano, R. C., M. Peñaherrera-Aguirre, A. J. Figueredo, & W. J. Jacobs (2022): "Comparing and contrasting rates of firearm homicides and suicides." *Evolutionary Psychological Science* pp. 1–17.

Appendix

Figures

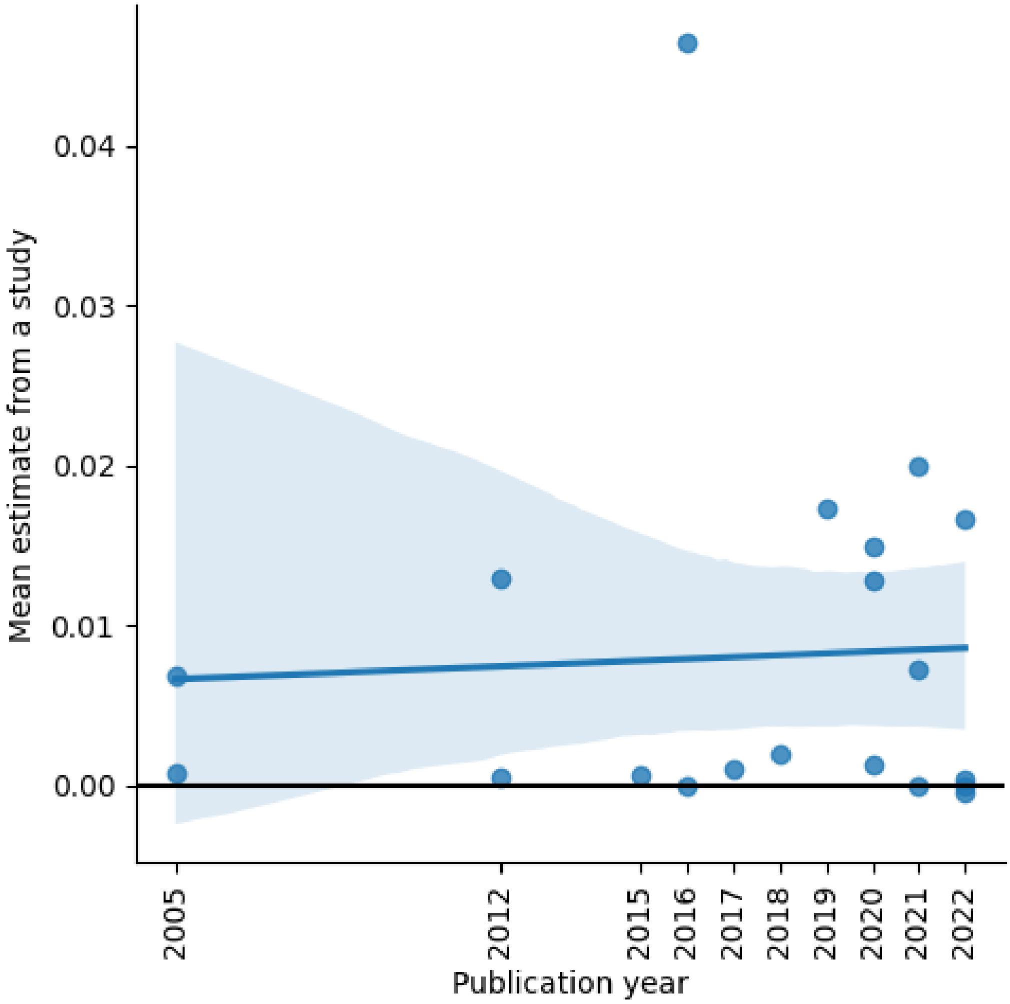

Figure 6: Mean estimate of temperature effect of homicide rate per study.

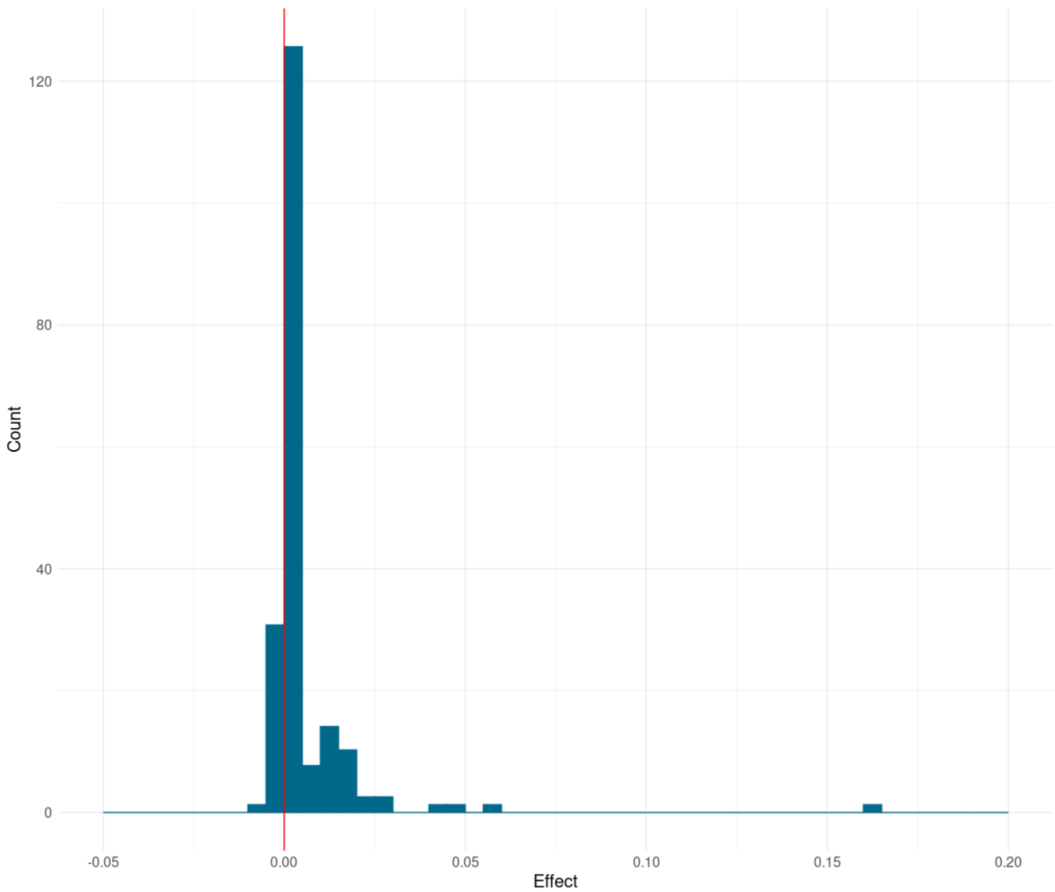

Figure 7: Distribution of collected effects.
Note: Plot shows distribution of all estimates. Red line stands for zero.

Tables

Variable	Description
Standard error (SE)	The reported standard error of the temperature effects on homicide rates.
Data characteristics	
Annual data	=1 if the data are in yearly frequency.
Monthly data	=1 if the data are in monthly frequency.
Daily data	=1 if the data are in daily frequency.
Mean temperature	=1 if temperature variable is measured as mean temperature.
Maximum (max) temperature	=1 if temperature variable is measured as maximum temperature.
Structural variation	
Rain variable	=1 if rain is variable is used.
$Temperature^2$ variable	=1 if $Temperature^2$ is variable is used.
Spatial characteristics	
USA	=1 the estimate is from USA country.
Asia	=1 the estimate is from Asia.
Other countries	=1 the estimate is from other country that USA or Asia.
Estimation methods	
OLS regression	=1 if the OLS estimation method is used.
Poisson regression	=1 if the Poisson regression method is used.
Fixed effects	=1 if the fixed-effects model is used.
Other method	=1 if other types of estimation are used.
Publication characteristics	
Sample size > 100,000	=1 if total number of observations used greater than 100,000.
Sample size < 100,000	=1 if total number of observations used smaller than 100,000.
Reviewed journal	=1 if a study is published in a peer-reviewed journal.
Citations	=Number of citations normalized by the number of years since the publication year.

Table 5: Description of the regression variables.

The number of citations has been collected from Google Scholar.

Table 6: Welch Two Sample t-test - effects

t-statistics	df	p-value	mean in group a	mean in group b
1.1214	205.13	0.2634	0.004829897	0.003306400

Note: Welch Two Sample t-test for winsorization. We cannot reject the null hypothesis, so there is no need for winsorization of effects estimates.

Table 7: Welch Two Sample t-test - standard errors

t-statistics	df	p-value	mean in group a	mean in group b
1.3871	196.26	0.167	0.003364928	0.002090939

Note: Welch Two Sample t-test for winsorization. We cannot reject the null hypothesis, so there is no need for winsorization of standard errors.

Table 8: Why estimates vary?

	PIP	Posterior mean	Posterior SD
Intercept	1.00	-0.344	NA
SE	1.00	1.64	0.05
Data characteristics			
Annual data	0.11	0.00	0.00
Monthly data	0.91	0.01	0.004
Daily data	0.11	0.00	0.01
Maximal temperature	0.15	0.00	0.00
Specification			
Rain	0.13	0.00	0.00
$Temperature^2$	0.13	0.00	0.00
USA	0.20	0.001	0.003
Asia	0.99	-0.02	0.005
Statistical approach			
OLS regression	0.45	-0.005	0.007
Poisson regression	0.27	-0.003	0.006
Sample size	0.33	0.00	0.00
Publication characteristics Citations	0.34	0.00	0.00
Reviewed journal	0.43	-0.004	0.006
Published year	0.20	0.00	0.00
Studies		20	
Observations		143	

Note: Table reports results of the *BMA* as displayed in Figure 5