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FACULTY OF SOCIAL SCIENCES
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Essays on Weather, Crime and Productivity

Dissertation thesis

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Declaration of Authorship

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Vojtech Misak

Abstract

The dissertation consists of three distinct empirical essays that examine how environmental factors, particularly weather conditions, influence crime and human productivity.

The first essay synthesizes the empirical literature on the relationship between temperature and homicide through a meta-analysis of 156 estimates from 20 studies. I systematically assess and correct for publication bias using linear, nonlinear, and Bayesian model averaging techniques and explore sources of heterogeneity in reported effects. After accounting for publication bias, I find no significant overall effect of temperature on homicide rates. The results reveal that studies using monthly data report larger estimates, whereas studies employing data from Asia or OLS estimation tend to find smaller effects.

The second essay investigates the mechanisms through which weather affects crime using daily panel data from the Czech Republic between 1996 and 2016. I analyze the effects of temperature, precipitation, visibility, and air pressure on several categories of crime, including homicide, assault, sexual crime, theft, and robbery, with further heterogeneity analyses by offender intoxication status, gender, and age. I find a positive relationship between temperature and most types of crime except homicide, with assault, theft, and robbery exhibiting an inverted U-shaped temperature relationship. Evidence suggests that alcohol consumption mediates the effects of temperature on sexual crime, theft, and robbery, and that temperature effects are more pronounced among male offenders for assault and theft.

The third essay examines the impact of temperature on productivity in professional soccer using match-level data from ten countries across three continents. I document nonlinear effects of temperature on several performance metrics. Warmer conditions increase attacking efficiency, leading to higher goal productivity and improved shot conversion rates, but simultaneously reduce defensive pressure and passing accuracy. Player aggression follows an inverted U-shaped pattern with respect to temperature. The effects are stronger in lower leagues and in teams from colder regions, which experience a sharper decline in passing volume when exposed to high temperatures.

JEL Classification	K10, K14, K32, K42, Q54, K49, Q54
Keywords	Weather, Crime, Productivity, Meta-Analysis, Publication Bias
Title	Essays on Weather, Crime and Productivity

Abstrakt

Disertační práce se skládá ze tří empirických esejů, které zkoumají, jak environmentální faktory, zejména počasí, ovlivňují kriminalitu a lidskou produktivitu.

První esej zkoumá empirickou literaturu o vztahu mezi teplotou a vraždami pomocí metaanalýzy 156 odhadů z 20 studií. Detekuji a koriguji publikační zkreslení pomocí lineárních, nelineárních metod a pomocí bayesovského modelového průměrování zkoumám zdroje heterogenity v publikovaných výsledcích. Po zohlednění publikačního zkreslení nenacházím žádný statisticky významný vliv teploty na počet vražd. Výsledky ukazují, že studie využívající měsíční data vykazují vyšší odhady, zatímco studie z Asie nebo studie používající metodu OLS mají tendenci nacházet menší účinky.

Druhá esej zkoumá mechanismy, prostřednictvím kterých počasí ovlivňuje kriminalitu, s využitím denních panelových dat z České republiky z let 1996 až 2016. Analyzuji vliv teploty, srážek, viditelnosti a tlaku vzduchu na několik kategorií kriminality, včetně vražd, ublížení na zdraví, sexuálních trestných činů, krádeží a loupeží, a dále provádím heterogenitní analýzy podle stavu intoxikace, pohlaví a věku pachatele. Zjišťuji pozitivní vztah mezi teplotou a většinou typů kriminality kromě vražd, přičemž u ublížení na zdraví, krádeží a loupeží se ukazuje převrácený tvar U ve vztahu k teplotě. Výsledky naznačují, že konzumace alkoholu zvyšuje vliv teploty na sexuální trestné činny, krádeže a loupeže a že efekt teploty je výraznější u mužských pachatelů ublížení na zdraví a krádeží.

Třetí esej zkoumá dopad teploty na produktivitu v profesionálním fotbale za použití dat na úrovni zápasů z deseti zemí na třech kontinentech. Zjišťuji nelineární vlivy teploty na několik ukazatelů výkonu. Vyšší teplota zvyšuje útočnou efektivitu, což vede k vyšší produktivitě v počtu gólů a lepší úspěšnosti střelby, ale zároveň snižuje obranné schopnosti týmu a přesnost přihrávek. Agresivita hráčů má ve vztahu k teplotě převrácený tvar U. Účinky jsou silnější v nižších ligách a u týmů z chladnějších regionů, které při vysokých teplotách zaznamenávají výraznější pokles počtu přihrávek.

Klasifikace JEL	K10, K14, K32, K42, Q54, K49, Q54
Klíčová slova	Počasí, Kriminalita, Produktivita, Meta-Analýza, Publikační zkreslení
Název práce	Eseje o Počasí, Kriminalitě a Produktivitě

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Chapter 1

Introduction

Understanding how environmental factors shape human behavior is a growing concern in both economics and public policy. Climate change is expected to alter temperatures and precipitation patterns worldwide, yet its social consequences are still not fully understood. While the economic literature has already focused on many aspects of environmental consequences on society, there are still gaps in our knowledge of how weather affects individual decision-making, aggression, and ultimately crime and productivity. These behavioral responses are of particular interest because they may translate small damages into large economic and social costs.

A growing body of interdisciplinary research suggests that weather conditions may influence human behavior through biological and psychological mechanisms. For example, ambient temperature has been linked to modulation of serotonergic neurotransmission and physiological discomfort that can increase impulsivity and aggression (Garza-Trevino (1994); Nelson & Chiavegatto (2001); Nelson (2005)), while temperature and precipitation also impact cognitive function, mood, and stress responses, which in turn shape social interactions and productivity outcomes (Nelson & Trainor (2007); Mazlan *et al.* (2020)).[1]

This dissertation contributes to the literature by examining how short-term and long-term weather variations influence human behavior, with a focus on aggression, crime, and productivity. It addresses the broad question of whether environmental conditions, particularly temperature and precipitation, affect individual decisions. By combining meta-analysis with evidence from micro-level

[1] A direct empirical test of specific biological mechanisms is generally limited by data availability. In this dissertation, such detailed mechanism-based testing is feasible only for alcohol presence in the context of weather and crime, which is examined in Chapter 3.

data, the thesis provides new evidence on the channels through which weather impacts life.

The first essay[2] conducts a meta-analysis of the effects of temperature on homicide rates. Homicides are widely regarded as the most reliable crime statistic for cross-country comparisons ((Mares & Moffett 2016)). I systematically collect 156 estimates from 20 studies and show that the positive temperature–homicide association reported in the literature is largely driven by publication bias. After correcting for this bias, the mean effect becomes statistically insignificant, suggesting that the true effect of temperature on homicide rates is smaller than previously believed. Moreover, analysis of heterogeneity among studies shows that studies using monthly data report larger estimates than daily-data studies. In addition, studies using data from Asia or the OLS estimation method tend to produce smaller estimates.

While the first essay synthesizes global evidence, the second essay turns to micro-level crime data to examine the short-term effects of weather on crime in the Czech Republic[3]. Using daily district-level data from 1996 to 2016, I analyze how temperature, precipitation, visibility, and air pressure affect violent and property crimes, distinguishing offenders by gender, age, and alcohol use. My results show a robust positive relationship between temperature and most crime categories (except homicides), with evidence of an inverted U-shaped relationship between temperature and assaults, thefts, and robberies. Precipitation has a crime-reducing effect, while alcohol consumption mediates the temperature–crime link, especially for sexual crimes and thefts. These findings highlight that crime is partly shaped by exogenous situational conditions and suggest that deterrence and policing policies could be made more effective by accounting for weather patterns.

The third essay explores the relationship between temperature and a related but distinct outcome: human productivity and aggression in a sport setting[4]. I exploit the unique setting of professional soccer, where performance can be measured relatively precisely and outcomes are highly salient. I collect a large dataset of matches from ten countries across three continents and investigate how temperature affects multiple performance metrics and aggression. I find that warmer conditions enhance attacking efficiency but reduce defensive control, while fouls follow an inverted U-shaped response to heat. The sensitivity

[2]Slightly different version was published as (Mišák 2024).
[3]Similar version published as (Mišák 2025a).
[4]Published in a similar version as (Mišák 2025b).

to temperature varies across leagues and climates, with teams from colder regions showing lower adaptability to high temperatures.

The three essays contribute to the understanding of how weather and climate influence human behavior. By combining meta-analysis, administrative crime data, and evidence from professional sport, I provide new insights into the mechanisms linking weather to crime and productivity. These findings are relevant for designing adaptive policies in the face of climate change, from crime prevention strategies to labor regulations, and suggest that weather-driven fluctuations in human behavior are an important channel through which environmental variables affect the economy.

Chapter 2

Does heat cause homicides? A meta-analysis

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 cannot conclude that there is a 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.

2.1 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.

Unlike existing reviews and meta-analyses on weather, climate, and violence (Corcoran & Zahnow (2022); Choi *et al.* (2024)), which cover a broad set of crime categories or provide mainly narrative syntheses, this paper focuses exclusively on homicide rates as the most comparable outcome across countries. Moreover, I apply recent meta-analytic techniques commonly used in economics, including extensive publication-bias corrections and methods that account for study heterogeneity, which have not been systematically employed in prior meta-studies on climate and interpersonal violence.

There is a large body of literature that examines the effect of weather on human behavior, decision making and possibly aggression. Pleasant weather influences human behavior in a positive way (most notably the effect of weather on the willingness to help others by (Cunningham 1979), or the effect of weather on the amount of tips in restaurants by (Rind 1996) or (Rind & Strohmetz 2001)). On the other hand, a number of studies suggest that as the temperature rises, the tendency for people to behave aggressively increases ((Kenrick & MacFarlane 1986) found a relationship between rising temperature and increased use of the driver's horn, or (Vrij *et al.* 1994) found that temperature also increases aggression among police officers). Moreover, (Mukherjee & Sanders 2021) examines the effect of weather on violence in prisons and concludes that high temperatures stimulate violent behavior among incarcerated persons.

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. (Mišák 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 $1 \circ \mathrm{C}$ 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 $1 \circ \mathrm{C}$ causes absolute increase in homicide rates by 0.0048, after correcting for publication bias, the effect is statistically insignificant. 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 2.2 describes how I collect data from primary studies and provides core dataset statistics.

Section 2.3 focuses on publication bias in the literature. Section 2.4 investigates the heterogeneity using Bayesian model averaging. Section 2.5 concludes the paper.

2.2 Data

2.2.1 Estimates collection

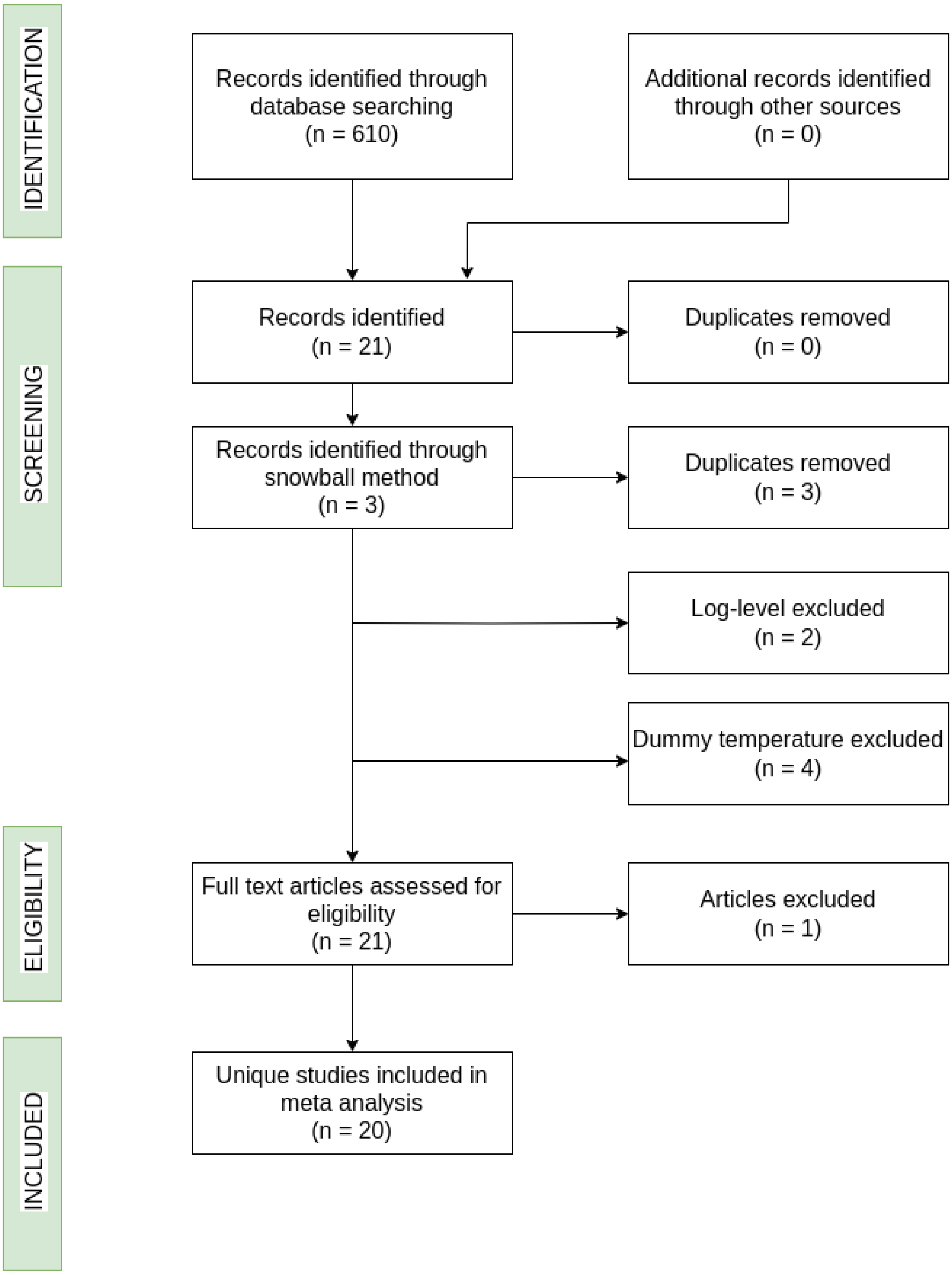
Following general guidelines for undertaking a meta-analysis such as (Field & Gillett 2010) or (Havránek *et al.* 2020) I did the following search for articles. Firstly, I searched "homicides+OR+murders+OR+crime+AND+temperature+ OR+weather" in Google Scholar. I then went through the first 610 studies manually. After that I did a snowball method[1] 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. Many excluded studies examined the effect of temperature on crimes other than homicide. Alternatively, they were qualitative studies that did not include empirical estimates. Moreover, 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 2.1. Table 2.1 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 2.3.

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

[1] Snowballing method involves manual screening of all articles that are listed in the references of a given paper.

Figure 2.1: PRISMA flow diagram.



following equation:

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

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

(Michel *et al.* 2016), (Trujillo & Howley 2021) and (Koppel *et al.* 2022) quantify the effect using an 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 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.

I did not collect log-level regressions because I am unable to recalculate these coefficients into level-level form[2]. In the field of metastudies, the partial correlation coefficient (PCC) method is sometimes used to compare these different estimates (in the field of economics for example (Doucouliagos 2005) or (Valickova *et al.* 2015)). However, for multiple reasons I decided not to use the PCC method. Firstly, the majority of existing studies use estimates from level-level regressions (recall Figure 2.1). Adding a small sample (only two articles as you can see in Figure 2.1) of estimates to the PCC method would not add much value to this paper. Second, the main focus of this meta-analysis is to determine the true effect of a 1'C increase in temperature on homicide rates. This is only possible by including papers built on level-level regressions. Finally, I didn't collect papers where the temperature was measured by a dummy variable that indicated some temperature threshold. These four articles cannot be used in any way in this meta-analysis.[3]

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

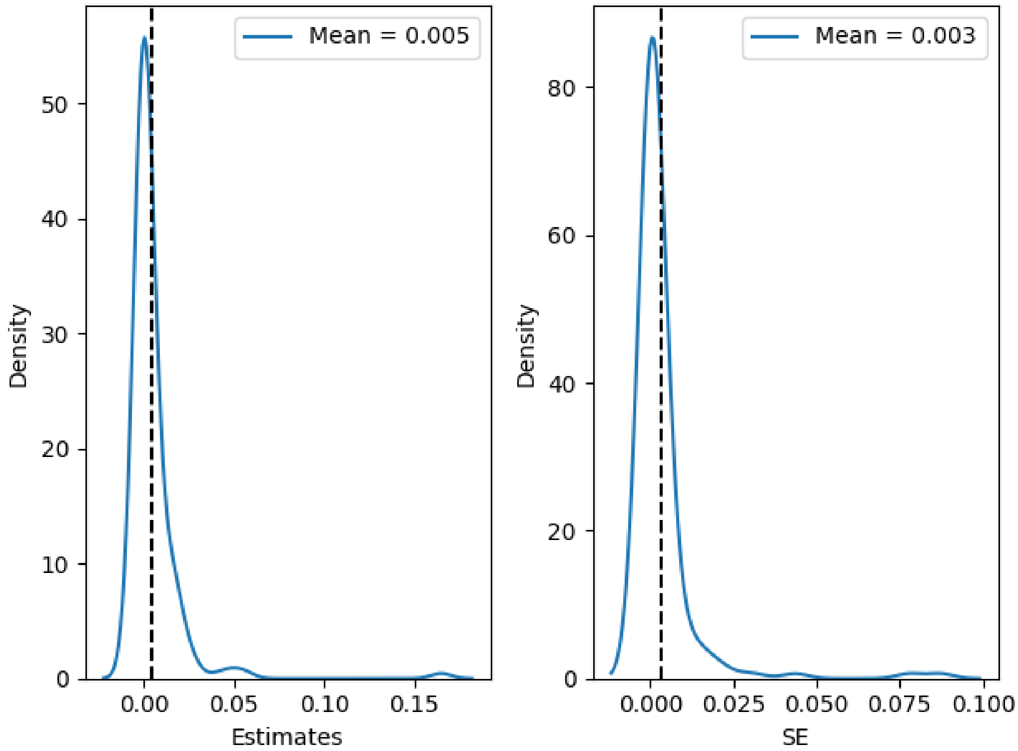
[2]The same applies to level-log or log-log regressions, but there were none in my case.

[3]Many excluded studies examined the effect of temperature on crimes other than homicide. Alternatively, they were qualitative studies that did not include empirical estimates.

2.2.2 Dataset statistics

The mean effect among all studies, as described in Table 2.4 and Figure 2.2, 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 2.2: 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.

Figure 2.3 shows the distribution of effects per each study. The plot suggests that the majority of estimates is positively distributed around zero[4]. The largest estimates are reported in the study by (Mares & Moffett 2016), while the lowest effects are reported by (Mišák 2022). Table 2.1 provides an overview of the collected studies and their characteristics. I draw several conclusions.

[4]Based on tests in Table A2.2 and Table A2.3 there is no need for winsorization of the data.

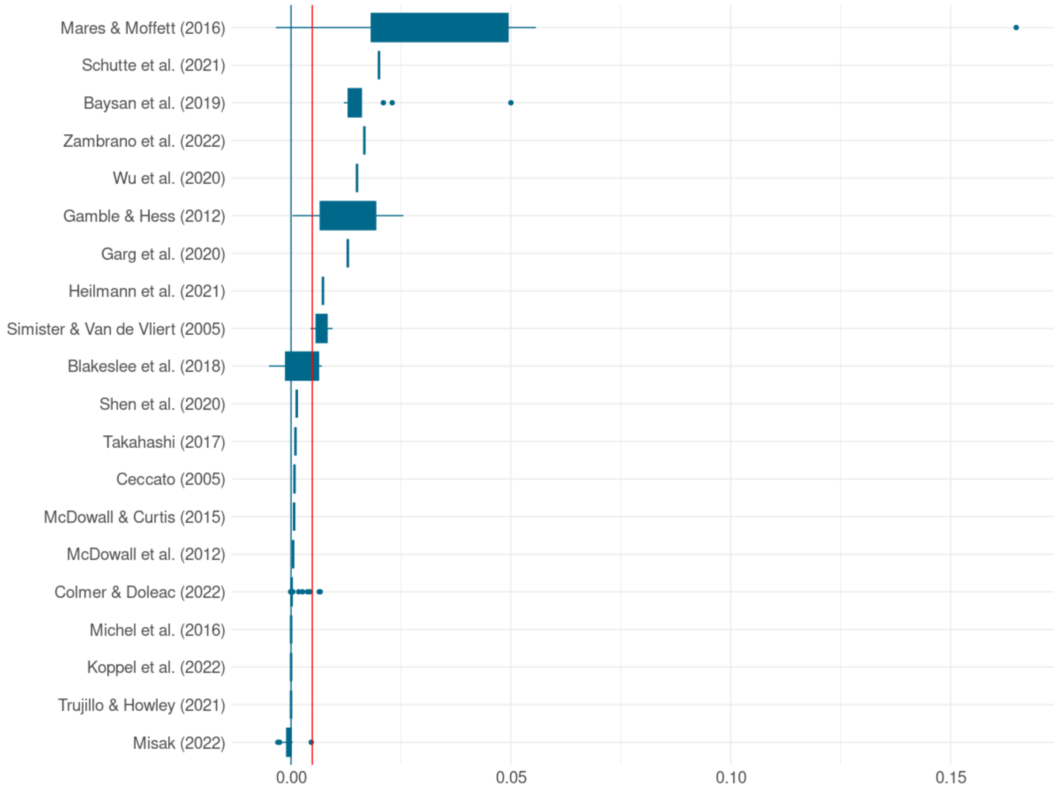
Firstly, the lengths of the examined datasets differ among studies. Authors such as (Zambrano *et al.* 2022) or (Gamble & Hess 2012) analyze homicide rates data from only one year, while (McDowall & Curtis 2015) examine data from 1960 to 2004. Secondly, the majority of studies use average temperatures, 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). Figure A2.1 shows the average estimate from each study across years. The number of studies on the effect of temperature on homicide rates seems to be increasing recently, which may be due to the growing interest in environmental research in recent years. It also appears that the average size of the estimates from the studies is increasing slightly over time. Figure A2.2 shows the distribution of effects as a histogram.

Table 2.1: Articles included in the meta-analysis.

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	2008 - 2013	monthly	M	1	0.00	0.00
(Mišák 2022)	Czechia	2005 - 2015	daily	A, M	23	-0.0005	0.001
(Schutte *et al.* 2021)	South Africa	2007-2014	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

A, M stands for average, maximum temperature, respectively.

Figure 2.3: 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.

2.3 Publication Bias

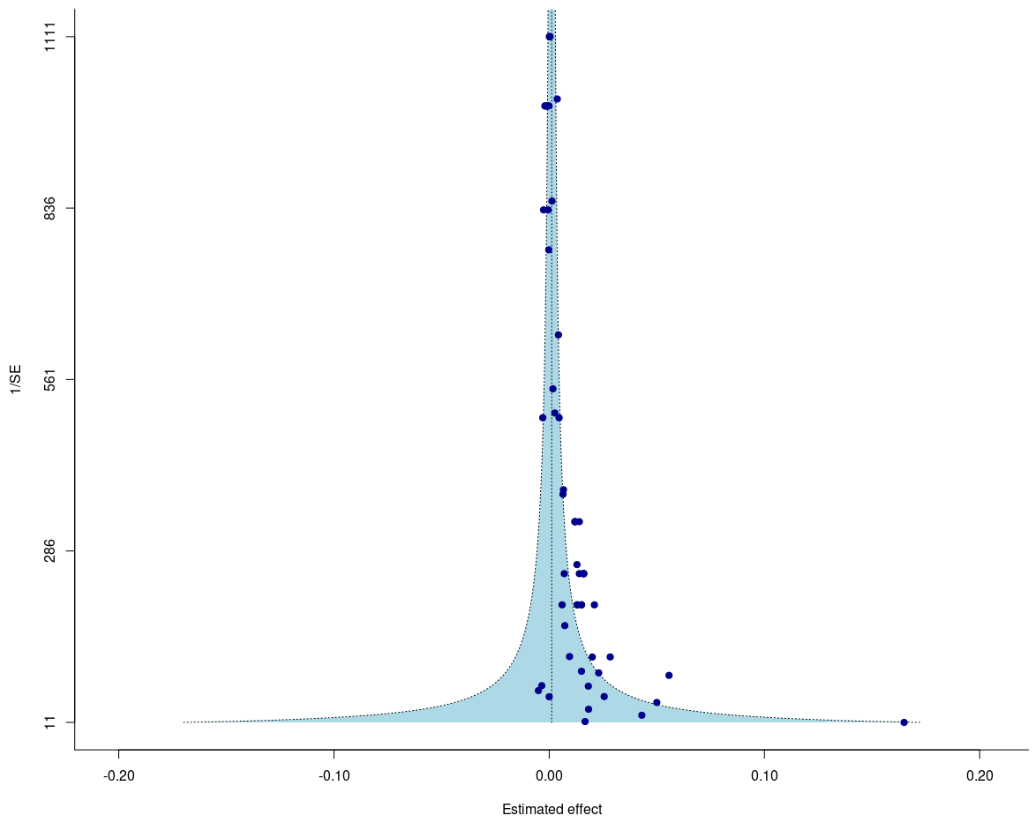
A standard method for checking the presence of publication bias is a funnel plot. In the case of no publication bias, estimates with higher precision will be plotted close to the average, while the less precise estimates are spread on both sides of the distribution. Any deviation from this shape indicates the presence of a publication bias. The funnel plot in Figure 2.4 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 2.2 and Table 2.3. Moreover, the shape of the funnel fence alone does not allow a clear conclusion to be drawn regarding publication bias, (Lau *et al.* 2006). One possible reason could be, for example, that 86 estimates come from paper by (Colmer & Doleac 2022) (see Table 2.1). This is also why additional methods to test for the presence of publication bias are necessary.

(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 2.2 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. I acknowledge that estimates from studies on data from the same country might be correlated with each other due to same data source. This might be the reason why the FE method provides higher SE estimate than other methods in Table 2.2, because fixed-effects model assumes that all collected estimates are drawn from the same population. (for example (Valickova *et al.* 2015)). Although the effect of temperature on the most serious crime (homicides), can be expected to be the same regardless of the country of origin of the offenders, other factors such as differences in population density, gun-control laws

Figure 2.4: Funnel plots.



and the prevalence of heat-mitigation technologies such as air conditioning can mitigate within a country. Therefor, in addition to the FE method, I also used random effects (RE) model that assumes the between-study heterogeneity of the estimates. 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 inverse number of estimates reported in the study. According to Table 2.1 number of estimates in each study vary from 1 to 86. The motivation for adding a study column is primarily to see if studies whose main research question is something other than the impact of temperature on homicide rates (especially the impact of heat on another crime category) are less likely to publish biased results. In other words, giving all studies equal weight regardless of the number of estimates in them serves as a robustness check of whether authors of studies with large numbers of estimates are tempted to bias their results. Neither standard error (i.e. the variable detecting publication bias) nor constant (i.e. the coefficient measuring the true effect among estimates) are statistically significant. This suggests that the asymmetric funnel plot, i.e. publication bias, is due to studies containing a large number of estimates.

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 2.2: Linear tests for publication bias

	OLS	**FE**	**RE**	**Precision**	**Study**	**Citations**
SE	1.1303*	2.0025***	1.579***	1.4808***	0.4782	1.5943***
(Publication bias)	0.568	0.659	0.084	0.325	0.835	0.079
Constant	0.00103	0.0000	0.0000	0.0000	0.0046	0.0007
(Mean beyond bias)	0.00162	0.0000	0.024	0.0000	0.0035	0.0018
Studies	20	20	20	20	20	20
Observations	156	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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.3: 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.

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 the exact form of the publication selection procedure. Moreover, the power of the linear test of publication bias increases with the number of studies. 20 studies, which I use in this meta-analysis, may therefore not be enough to avoid a possible type I error (see (Peters *et al.* 2006)).Therefore, in addition to linear tests for publication bias in Table 2.2, I employ three non-linear tests as displayed in Table 2.3. 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. The usual approach involves making conclusions based on all the data and research findings available. However, in cases where scientific literature is affected by publication bias, excluding a significant portion of empirical results can paradoxically enhance statistical inference and estimation.

Second, stem-based approach by (Furukawa 2019) emphasizes the importance of conducting highly accurate studies to generate meta-analysis estimates. This is because conventional models indicate that studies with greater precision are less susceptible to publication bias. Generally, more precise studies are considered more trustworthy, reducing the likelihood of not publishing them. This method expands upon the "top10" estimator, which focuses on the most precise 10% of studies, as suggested by (Stanley *et al.* 2010). (Furukawa 2019) chooses the optimal n most precise studies to include by minimizing the Mean Squared Error of the estimates. Methods by (Stanley *et al.* 2010) and (Furukawa 2019) can be useful if publication bias causes situations where only the very precisely estimated null effects get published.

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 2.2 and Table 2.3, 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 0.003, which is 62.5% of the 0.0048, which is the average of all estimates. Therefore, it seems that effect of heat on homicide rates is not statistically significant or the effect is smaller than commonly thought.

The distribution of t-statistics in the Figure A2.4 across estimates is presented to visually assess potential discontinuities around conventional significance thresholds. Neither visual inspection nor the formal caliper test following Gerber & Malhotra (2008) indicates suspicious clustering around the 1%, 5%, or 10% levels, suggesting no evidence of p-hacking.

2.4 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 2.1).

Table 2.4 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 2.4, 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

Table 2.4: Summary statistics for different subsets of collected literature.

	No. of studies	No. of est.	*Unweighted* Mean	*Unweighted* Variance	*Weighted* Mean	*Weighted* 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

Note: 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 A2.1.

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 2.4 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 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.

The considered types of heterogeneity capture distinct mechanisms through which temperature effects on homicide rates may vary across studies. Data characteristics reflect the degree of temporal aggregation and thus the ability to identify responses of homicide rates to temperature. Structural variation accounts for non-linearities and correlated weather variables, which can attenuate estimated effects. Spatial characteristics proxy for institutional and climatic contexts that condition the temperature–homicides relationship. Finally, publication characteristics capture systematic differences in reported estimates: high-impact journals may favor studies with stronger or more significant effects, while regressions based on very large samples might produce different effect estimates than those based on smaller samples.

2.4.1 Bayesian model averaging

The goal of this subsection is to analyze which variables, as listed in Table 2.4, explain the heterogeneity in the estimates reported in the literature. Diversity among study characteristics can influence the observed bias. To elaborate, even in the absence of selective reporting in the literature, this diversity has the potential to cause asymmetry in the funnel plot. 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 2.4 will decrease the overall precision of the results. (Steel 2020) recommends addressing this model uncertainty problem using Bayesian model averaging (BMA).[5] Bayesian model averaging with a dilution prior is employed as the main tool to address both model uncertainty and collinearity among study characteristics, in line with recent guidelines for meta-analysis in economics Havránek *et al.* (2020); Irsova *et al.* (2024). In addition, a linear regression model is estimated as a frequentist benchmark, which serves to verify that the qualitative conclusions are not driven by the Bayesian framework but remain robust across different inferential approaches. 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:

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

Bayesian Model Averaging (BMA) tackles the uncertainty in the model by examining numerous models with varying covariate selections, as proposed by (Raftery 1995). Essentially, BMA involves estimating a multitude of regressions using different combinations of explanatory variables. Consequently, it calculates a weighted average across all potential combinations of explanatory variables ((Zeugner & Feldkircher 2009)), employing posterior model probabilities as the weighting mechanism. These probabilities, derived from Bayes’ theorem, are proportional to the product of the integrated likelihood of the model (which captures the probability of the observed data given the model) and the prior model probability. The resulting product is then divided by the

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

sum of integrated likelihoods across all regression models. The posterior model probability assesses how well the model fits the data, while the prior model probability reflects the researcher's initial beliefs about the likelihood of a particular model before taking the data into account, (Zeugner 2011).

I included 11 variables that, according to the discussion in Section 2.4 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:

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

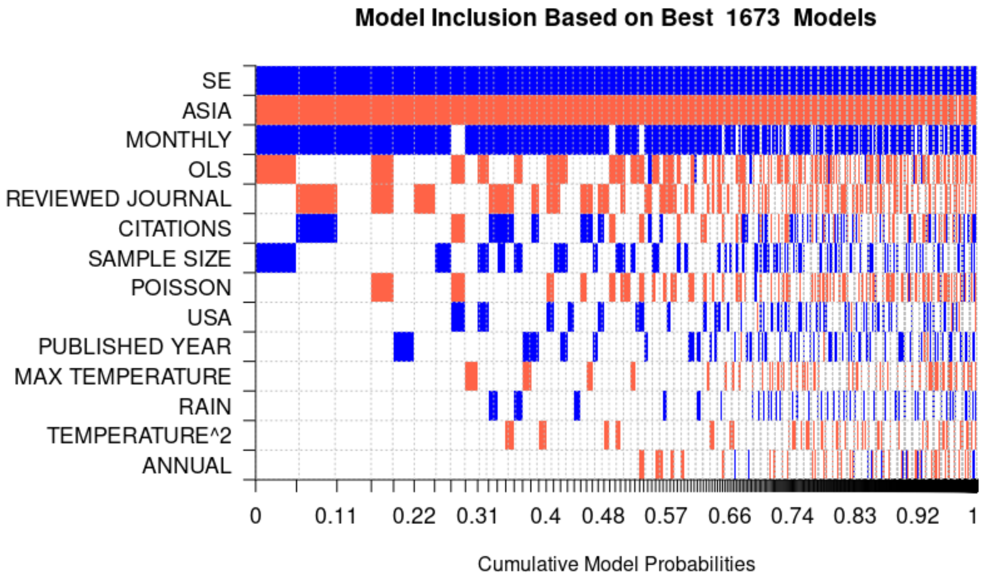
where HR_{ji} stands for j-th homicide rate estimate as reported in i-th study, X_{ji} stands for explanatory variables and SE stands for standard error. Coefficient γ_0 stands for the mean effect corrected for publication bias, while γ_1 denotes the direction of the publication bias, similarly to the linear test for the funnel plot asymmetry discussion in Section 3.5. 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 2.5 and Table A2.4.

Note that dummy variables are treated in BMA as in classical regression. In other words, it is the difference in the HR_{ji} between those with 1 and those with 0 values of that dummy variable, ceteris paribus.

On the vertical axes explanatory variables as described in Table A2.4 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.

(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 3.5. Moreover, I argue that studies conducted using monthly data produce higher estimates. This is in line with scholars such as (Mišák 2022) or (Ranson 2014) who mention differences between short-run and long-run temperature effect estimates

Figure 2.5: Model inclusion in Bayesian model averaging



The figure displays the results of the benchmark BMA model as reported in Table A2.4.

on crime. Moreover, OLS regression techniques leads to lower 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). To ensure that the effect of lower estimates from Asian countries is not driven by the fact that these effects are estimated on monthly data I provided a robustness check by adding $Asia * Monthly$ variable into BMA analysis (see Figure A2.3 and Table A2.5). Based on the results, it seems that the effect for the Asian estimates remains significant and negative.

2.5 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.[6]

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 there is not enough evidence that higher temperature causes an increase in homicide rates.

Appendix

Figures

[6] This does not imply that temperature is unrelated to violence in all contexts, but rather that the existing evidence does not support a strong or systematic effect on homicide rates, which is relevant for policy debates linking climate change to violent crime.

Figure A2.1: Mean estimate of temperature effect of homicide rate per study.

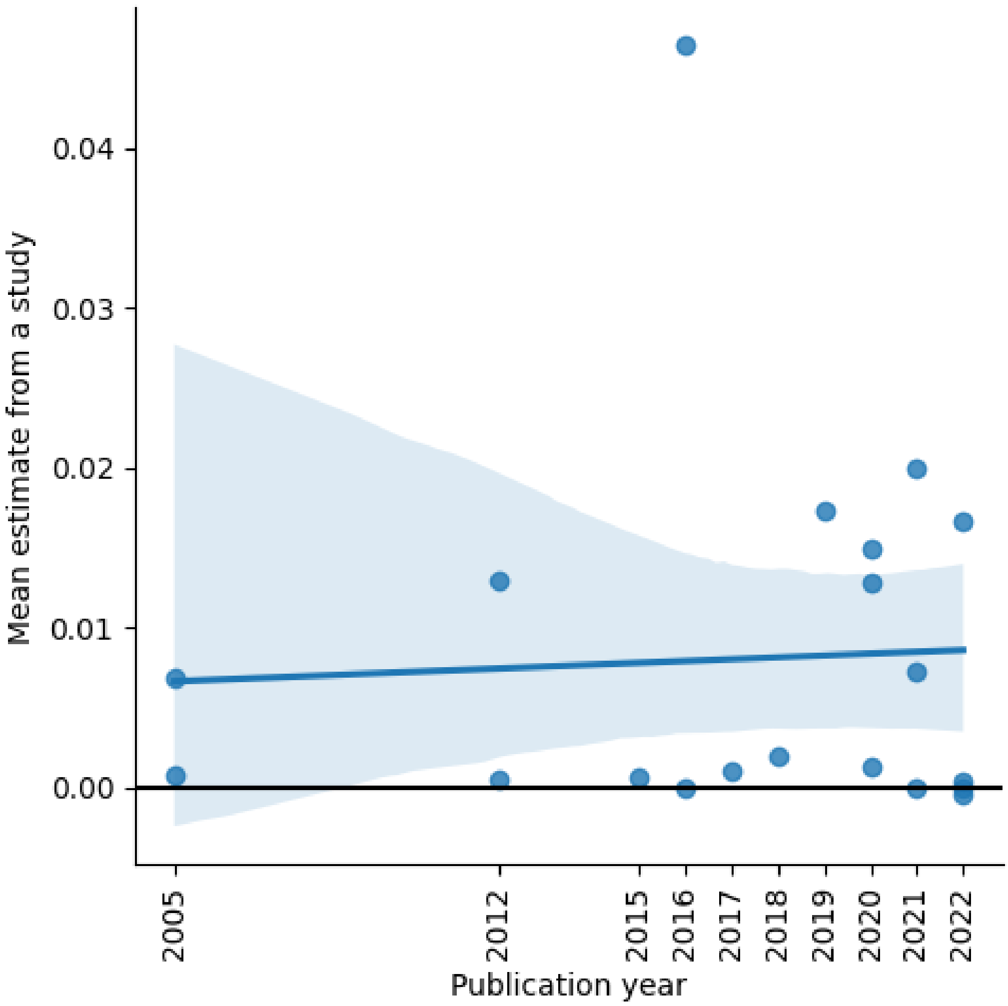
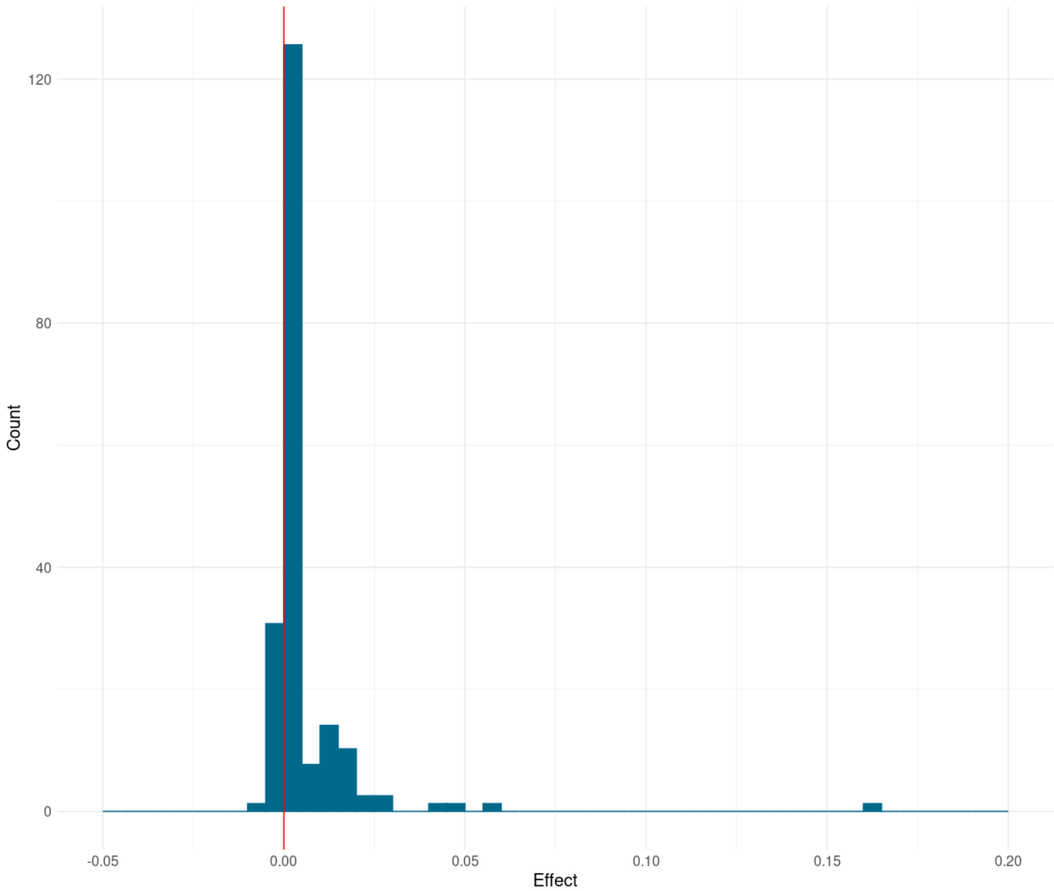
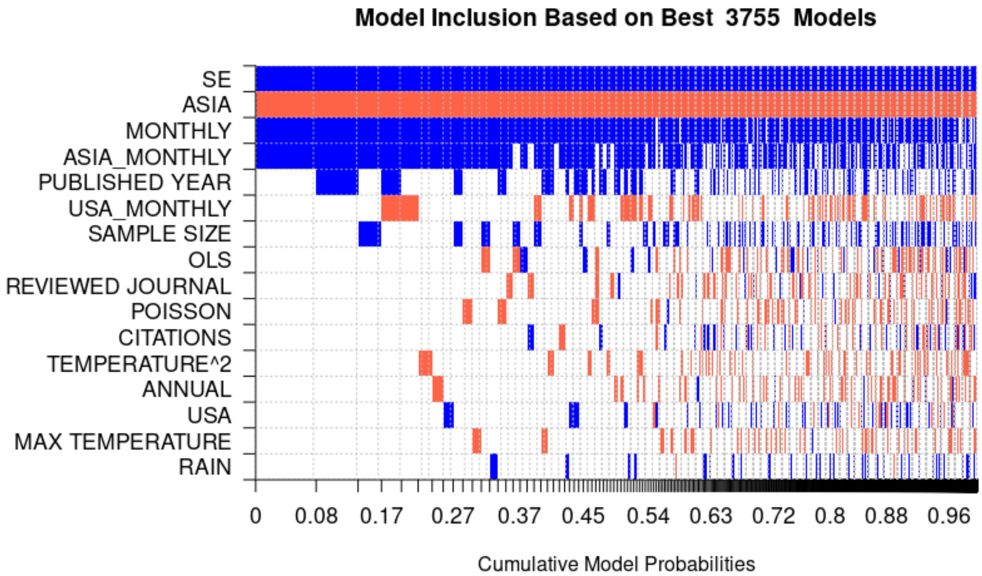


Figure A2.2: Distribution of collected effects.



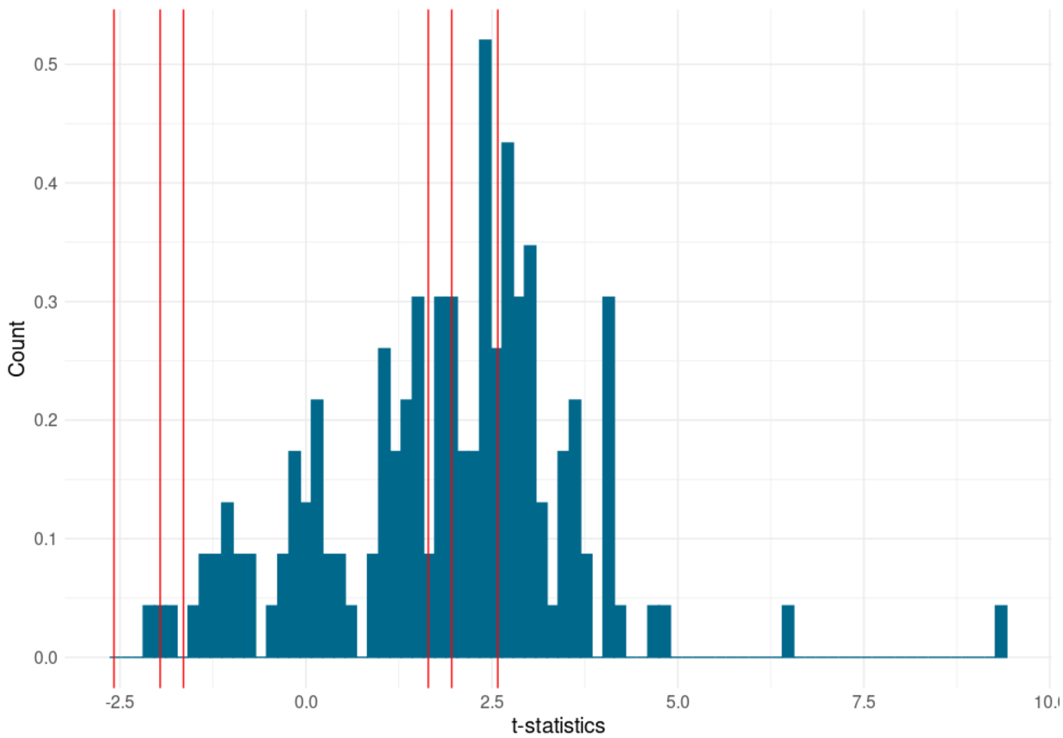
Note: Plot shows distribution of all estimates. Red line stands for zero.

Figure A2.3: Model inclusion in Bayesian model averaging.



Note: The figure displays the results of the BMA robustness check model including $Asia * Monthly$ *as reported in the Table A2.5.*

Figure A2.4: Distribution of t-values.



Note: Vertical red lines correspond to the 1%, 5%, and 10% significance levels.

Tables

Table A2.1: Description of the regression variables.

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.

Note: The number of citations has been collected from Google Scholar.

Table A2.2: 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 A2.3: 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 A2.4: Why estimates vary?

	PIP	Posterior mean	Posterior SD	OLS estimate	OLS SD
Intercept	1.00	-0.344	NA	-0.002*	0.001
SE	1.00	1.64	0.05	1.635***	0.06
Data characteristics					
Annual data	0.11	0.00	0.00		
Monthly data	0.91	0.01	0.004	0.01***	0.002
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	-0.02***	0.004
Statistical approach					
OLS regression	0.45	-0.005	0.007	-0.007***	0.003
Poisson regression	0.27	-0.003	0.006		
Sample size	0.33	0.00	0.00	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		20	
Observations		143		143	

Note: Table reports results of the *BMA* as displayed in Figure 2.5. SD stands for standard deviation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2.5: Why estimates vary? - Robustness check

	PIP	Posterior mean	Posterior SD	OLS estimate	OLS SD
Intercept	1.00	-0.475	NA	-0.002*	0.001
SE	1.00	1.66	0.08	1.655***	0.06
Data characteristics					
Annual data	0.14	0.00	0.00		
Monthly data	0.96	0.01	0.003	0.01***	0.002
Monthly data * Asia	0.79	0.02	0.01	0.02***	0.008
Monthly data * USA	0.24	0.00	0.00		
Maximal temperature	0.12	0.00	0.00		
Specification					
Rain	0.10	0.00	0.00		
$Temperature^2$	0.14	0.00	0.00		
USA	0.13	0.00	0.00		
Asia	0.99	-0.02	0.006	-0.03***	0.005
Statistical approach					
OLS regression	0.20	-0.001	0.004	-0.005*	0.003
Poisson regression	0.16	-0.00	0.003		
Sample size	0.24	0.00	0.00	0.00**	0.00
Publication characteristics					
Citations	0.14	0.00	0.00		
Reviewed journal	0.17	0.00	0.003		
Published year	0.33	0.00	0.00		
Studies		20		20	
Observations		143		143	

Note: Table reports results of the *BMA* as displayed in Figure A2.3. SD stands for standard deviation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2.6: Caliper test

Significance level	Critical value	Caliper	Test statistic	p-value
1%	2.58	0.1	0.500	0.342
1%	2.58	0.2	0.558	0.441
1%	2.58	0.3	0.500	0.397
5%	1.96	0.1	0.267	0.059
5%	1.96	0.2	0.464	0.301
5%	1.96	0.3	0.490	0.372
10%	1.645	0.1	0.538	0.282
10%	1.645	0.2	0.483	0.322
10%	1.645	0.3	0.450	0.316

Notes: The table reports test statistics and corresponding p-values from the caliper sensitivity test. Critical values correspond to the 1%, 5%, and 10% significance levels. Different caliper widths are used to assess the robustness of the matching procedure.

Chapter 3

Exploring the Mechanisms Between Weather and Crime: Insights from the Czech Republic

Abstract

This study investigates the mechanisms through which weather influences crime. Utilizing daily panel data from the Czech Republic spanning 1996 to 2016, I analyze the impact of outdoor temperature, precipitation, visibility, and air pressure on incidences of homicide, assault, sexual crime, theft, and robbery. These effects are further examined by exploiting variation in offenders' intoxication status as a potential mediating mechanism, and by analyzing heterogeneity across gender and age groups. A positive relationship between temperature and crime is observed across all categories except homicide. Additionally, an inverted U-shaped relationship is identified between temperature and rates of assault, theft, and robbery. The findings suggest that alcohol consumption mediates the influence of temperature on sexual crime, theft, and robbery rates. Furthermore, temperature effects are more pronounced for male offenders in cases of assault and theft. Lastly, the age of offenders does not appear to significantly affect the weather-crime relationship.

3.1 Introduction

An increasing body of literature suggests that weather impacts peoples' mood and human behavior (most notably (Rind 1996) or (Jacob *et al.* 2007), for recent studies see e.g., (Jahn 2015), (Ettema *et al.* 2017) or (De Groot 2019)). The link between weather and crime has been investigated for decades, with early studies such as (Baron 1972) and (Anderson 1987) already exploring the relationship between temperature and aggression. Nevertheless, the topic remains open, as researchers continue to examine its context-specific effects, and robustness across crime categories and regions. From the existing literature, it appears that weather affects all types of crime (violent and property), except homicides (see a meta-analysis by (Mišák 2024)). Studies such as (Gamble & Hess 2012), (Butke & Sheridan 2010) or (Blakeslee *et al.* 2021) find a link between temperature or rain and rates of assaults and sexual crimes. (Ranson 2014) focuses on future climate change impacts on increase in crime rates in the USA, while (Horrocks & Menclova 2011) investigates temperature, rain and the Nor'wester wind, concluding that there is a causal link between weather and crime in New Zealand. The same causal link is found in studies on property crime, such as thefts or burglaries (e.g., (Peng *et al.* 2011) or (Linning *et al.* 2017)). Finally, some authors, such as (Ishak 2022) and (Blakeslee & Fishman 2018), explore weather-induced shocks to agricultural production and their impact on crime in developing countries, offering a macro-level perspective.

The primary objective of this study is to address the existing gaps in the literature. To date, empirical research has not made a clear distinction between the various channels through which weather may influence crime. It is reasonable to assume that the established theories explaining how weather influences crime are robust and applicable to various groups of offenders. To bridge this gap, the study conducts an investigation into the short-term daily effects of weather on crime using daily district-level data from the Czech Republic, a high-income Central European country, spanning the years 1996 to 2016. The focus of the analysis is to examine the influence of weather on criminal behavior among different demographics, including men and women, offenders under the influence of alcohol, and offenders from various age groups. To offer a comprehensive view, this paper expands on the current body of literature by examining four specific weather characteristics: mean daily temperature, total precipitation, visibility, and air pressure. While a majority of existing studies predominantly use data from the United States (as discussed in (Mišák 2024), and (Mares & Moffett 2016)), studies utilizing annual data from developing countries have often yielded different results regarding the weather-crime nexus (Mišák 2024). This suggests that the geographical and temporal context, particularly the focus on short-term daily effects in a developed country like the Czech Republic, may offer more relevant and nuanced insights into these dynamics.[1] Therefore, this research contributes to the academic discourse by providing additional evidence from jurisdictions that are not typically the focus of such investigations.

The study's findings reveal a positive linear relationship between temperature and crime across all crime categories, except homicide. A concave (inverted U-shaped) relationship with temperature was identified for assault, theft, and robbery. Alcohol consumption significantly mediates the influence of temperature on the incidence of sexual crimes, thefts, and robberies. The impact of temperature on assault and theft rates is more pronounced among male offenders. The age of offenders does not appear to have a statistically significant effect on the relationship between weather and crime. Precipitation was found to diminish the occurrence of assaults and sexual crimes, while visibility increases both assaults and thefts. Air pressure did not exhibit a consistent effect on crime rates across the analyzed categories.

These findings underscore the complex interplay of weather, individual characteristics, and criminal behavior, offering policy-relevant insights. Importantly, the observed associations between temperature, environmental factors, and crime suggest that situational conditions may play a meaningful role in shaping criminal behavior, alongside more stable individual characteristics. This has important implications for the economics of crime: if exogenous factors such as weather systematically shift the probability of offending, optimal deterrence parameters (e.g., policing intensity or sentencing severity) may need to vary with environmental conditions. For example, increased police presence during hotter days or large public events in warm weather could mitigate temperature-induced crime surges.

Moreover, the mediating role of alcohol in several crime categories highlights the importance of integrating public health and law enforcement strategies. Targeted regulation of alcohol availability or consumption in high-temperature contexts (e.g., through time-limited sales or sobriety checkpoints) may help reduce the incidence of temperature-sensitive crimes. Recognizing these dynamics allows for the development of more adaptive and efficient crime prevention policies, particularly in the context of climate change and rising global temperatures.

[1] Given that most studies originate in the Northern Hemisphere, where alcohol consumption and holiday patterns differ from those in the South ((Phakula *et al.* 2024; Bellis *et al.* 2015)), results from Central Europe add valuable perspective.

3.2 Theoretical Background

There are several possible justifications in the literature as to why weather influences human aggression and crime. The Negative Affect Escape (NAE) model (Bell 1992) posits an inverted U-shaped relationship between temperature and crime, suggesting that extreme heat generates discomfort, which in turn fuels aggressive behavior. In contrast, the General Affect (GA) model (Anderson & Anderson 1998; Rotton & Cohn 2000) proposes a monotonic, often linear, relationship where the effect of heat on violence is driven by interactions between season and temperature. These two models primarily focus on the physiological and psychological impact of temperature on individual aggression. Conversely, the Routine Activity (RA) model (Cohen & Felson 1979; Felson 1987) explains the weather-crime link through opportunity and social interaction. It argues that pleasant weather conditions increase the likelihood of motivated offenders, suitable targets, and the absence of capable guardians converging in time and space, thereby elevating crime risk. The distinct mechanisms proposed by these models—individual affect versus situational opportunity—underscore the importance of empirically distinguishing their applicability across various crime types and offender demographics.[2]

Beyond these theories, the role of alcohol consumption as a transmission channel is crucial. It is widely accepted that alcohol increases aggressive behavior and violent crime (Speer *et al.* 1998; Markowitz 2005; McClelland & Teplin 2001). Given that weather, especially temperature, impacts alcohol consumption (Ventura-Cots *et al.* 2019; Hensel *et al.* 2021), alcohol acts as another indirect pathway between weather and crime (Otrachshenko *et al.* 2021). Notable examples include the work of (Wennman *et al.* 2019), who found that women were significantly more physically active than men across all age groups up to 65 years, and (Wilsnack *et al.* 2000), who reported that men consume more alcohol than women.

While the NAE, GA, and RA models primarily focus on temperature and social interaction, including air pressure as a weather characteristic is important. Unlike temperature or precipitation, air pressure does not directly shape outdoor activity but may influence behavior through physiological or psychological discomfort. Changes in air pressure have been linked to various effects in humans, such as headaches, mood changes, and even joint pain, which could

[2] See also (Ceccato 2005), who reports evidence consistent with a U-shaped temperature-homicides relationship in São Paulo within the framework of routine activity theory.

potentially influence individual affect or tolerance for discomfort (i.e. (Denissen *et al.* 2008)). Although less commonly explored in crime literature compared to temperature or precipitation, fluctuations in air pressure could subtly contribute to the "negative affect" mechanism (as in NAE or GA models) or indirectly influence individuals' willingness to engage in routine activities, thus warranting its inclusion in a comprehensive analysis.

3.3 Data

I investigate daily data from 80 districts in the Czech Republic (a landlocked country in Central Europe of 10.5 million people, and a member of EU, NATO and OECD) from 1996 to 2016. Crime categories and corresponding data summary is provided in Table 3.1 and Table 3.2.

3.3.1 Crime

Table 3.1 shows how offenses are assigned to the five categories, while Table 3.2 provides summary statistics of these categories.[3] The dependent variable is constructed as the number of offenses committed per 1,000,000 population per day and per district. Only for those crimes for which an offender has been identified can we tell whether the offender was under the influence of alcohol, whether the offender was male or female, and how old the offender was. From a methodological point of view, I discuss this issue in more detail in Section 3.4.

Table 3.1: Categories of crime data

Aggregated crime category	**Corresponding Subcategories**
Homicides	Robbery murder, Sexual murder, Bounty murder, Murder motivated by personal relationships, Infanticide, Other murders
Assaults	Manslaughter, Kidnapping, Injury, Taking hostages, Threatening, Extortion, Trespassing, Maltreatment
Sex crimes	Rape, Sexual coercion, Sexual abuse
Thefts	Larceny, Car theft, Simple theft
Robbery	Simple robbery, Bank robbery

[3]Crime data come from the crime statistics system of the Police Presidium of the Czech Republic ("Evidenčně statistický systém kriminality Policejního prezidia ČR").

Table 3.2: Crime categories statistics

	Homicides			**Assaults**			**Sex crimes**			**Thefts**			**Robberies**		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
All	0.147	0	9	24.97	0	390	2.244	0	90	313.68	9	1230	8.66	0	47
Alcohol	0.05	0	4	3.821	0	62	0.17	0	6	2.399	0	39	0.351	0	11
Non-Alcohol	0.056	0	7	15.3	0	265	1.412	0	75	86.605	0	640	4.475	0	35
Men	0.117	0	9	18.014	0	315	1.588	0	80	84.689	0	637	4.644	0	40
Women	0.018	0	2	1.666	0	25	0.038	0	5	6.277	0	55	0.307	0	9
Age 0 - 21	0.019	0	4	4.20	0	99	0.546	0	34	38.082	0	424	2.46	0	33
Age 21 - 30	0.032	0	6	5.53	0	52	0.37	0	30	29.11	0	195	1.479	0	32
Age 30 - 50	0.062	0	5	8.137	0	192	0.568	0	41	21.44	0	156	0.937	0	12
Age 50 +	0.023	0	4	1.812	0	70	0.141	0	12	2.328	0	22	0.072	0	5

Note: The table reports mean, minimum, and maximum values per 1,000,000 people per day and district. Categories such as Alcohol/Non-Alcohol, Men/Women, and age groups are not additive at the district-day level; therefore, maximum values in the "All" category do not equal the sum of maxima across subcategories.

3.3.2 Weather

All weather data come from the OpenWeather API. [4]. OpenWeather data are derived from a combination of multiple meteorological sources, including surface weather stations, satellite observations, radar systems, and numerical models such as GFS and ECMWF. These inputs are integrated into OpenWeather's proprietary OWHL model, which also incorporates information from national meteorological agencies and airport METAR reports, ensuring a comprehensive and frequently updated dataset for weather monitoring, Yanes (2011).

According to Figure 3.1 and Table 3.3, the weather data correspond to the Central European climate in a landlocked country without substantial weather extremes. The average temperature is 9.28 °C, with the first and third quartiles spanning from 2.93 °C to 15.81 °C. Moderate values are also observed for air pressure and visibility. Based on Figure 3.2, rainy days typically feature mild precipitation, rarely exceeding 50 mm per day. Finally, Figure A3.1 shows the average monthly temperatures over several years, illustrating regular seasonal variation.

[4] https://openweathermap.org/api

Figure 3.1: Weather variables histograms

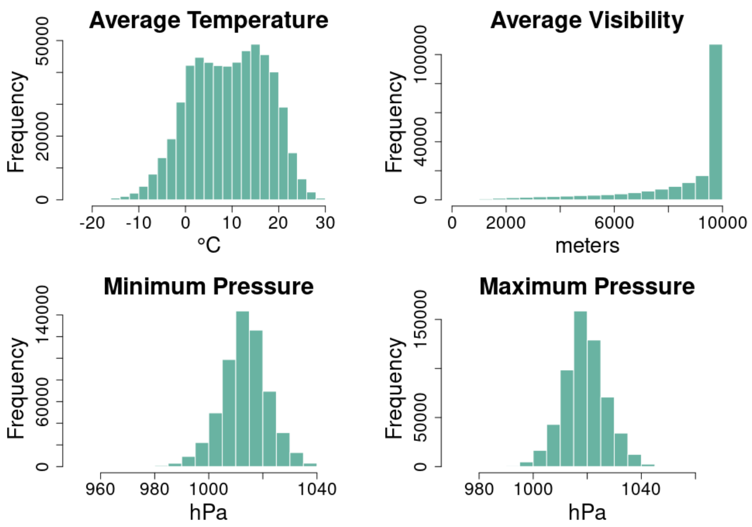


Figure 3.2: Histogram of precipitation levels on rainy days

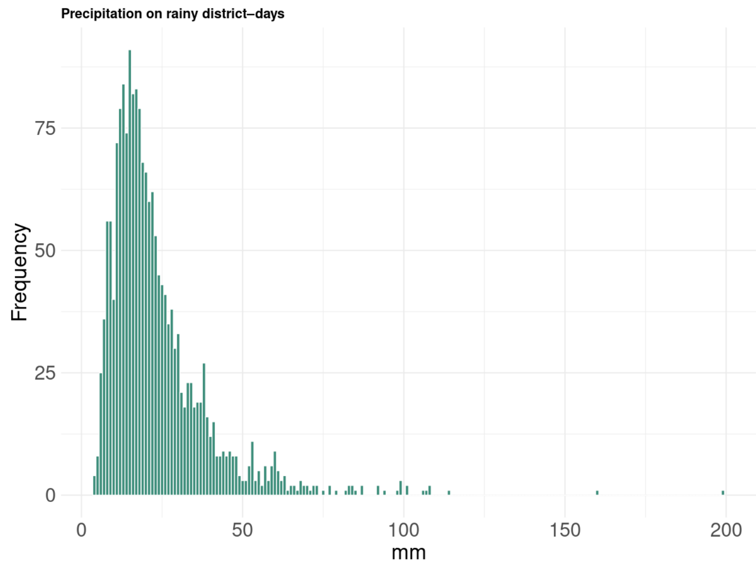


Table 3.3: Weather statistics

	Minimum	**Maximum**	**Mean**	Q_1	Q_2	Q_3
Average Temperature	-22.68	31.15	9.28	2.93	9.46	15.81
Total Precipitation	0	198.6	0.07	0	0	0
Average Visibility	81.25	10000	8733	8254	9791	10000
Maximal Air pressure	972	1099	1019	1015	1020	1025
Minimal Air pressure	950	1046	1014	1009	1014	1019

Note: The table shows the daily statistics in each district of weather categories analyzed in the article. Q_1 , Q_2 , Q_3 denotes quantiles 1, 2 and 3 respectively. Units: Average Temperature in degree Celsius, Total Precipitation in milliliters, Average Visibility in meters, Air pressure in kPa.

3.4 Identification strategy

The identification strategy is motivated by my goal to estimate the causal short-term effects of weather on crime rates. The estimated regression has the following form:

$$crime_{i,d} \sim \beta_0 + \beta_1 \cdot weather_{i,d} + \beta_2 \cdot FE_{i,d} + u_{i,d}$$

Where $crime_{i,d}$ denotes total number of crimes committed per 1,000,000 people, $weather_{i,d}$ stands for the weather category, FE are the fixed effects and u is the error term, all in district i and day d. To best capture the short-term effects between weather and crime, I used district, day of the week, month of the year and year as fixed effects. The identifying variation comes from within-district, day-to-day fluctuations in weather, which are plausibly exogenous to short-run changes in economic activity and other socio-economic factors. These factors evolve at lower frequencies and are absorbed by the rich set of fixed effects.

The study examines the impact of weather on crime, focusing on alcohol consumption among offenders as a potential mediating channel, and on age and gender as sources of heterogeneity in weather effects. The analysis is complicated by the fact that the total number of crimes committed under the influence of alcohol, differentiated by gender and age, is not directly observable. These characteristics are only recorded when the offender is identified, meaning the observed total crimes are diminished by the clearance rates.[5] Consequently, few methods have been developed to address this limitation and accurately assess the relationship between weather, alcohol influence, and the demographic characteristics of offenders.

I estimate each regression for all crimes committed regardless of whether the offender was detected by the police. The dependent variable is total number of crimes per district. This allows me to obtain a general estimate of the effect of weather on crime, in the same vain as similar studies from other countries (discussed in Section 3.1).

I test the statistical effect of temperature on crime rates between categories (i.e. all crimes together vs alcohol, gender and age groups) using the following

[5]In other words, no such model $y_{i,d} \sim \beta_1 \cdot X_{i,d} + \beta_2 \cdot D_{i,d} + \beta_3 \cdot X_{i,d} \times D_{i,d} + u_{i,d}$ is possible. The independent variables on the right hand side remain the same, the dependent variable changes, i.e. crime.

Table 3.4: Clearance rate

Homicides	88.5 %
Assaults	78.2 %
Sex crimes	72.0 %
Thefts	29.5 %
Robberies	56.0 %

three methods:

Firstly, I assume that the ratio between all crimes committed, irrespective of their clearance rate, and each subcategory of crimes remains constant over time (i.e., the number of crimes committed under the influence of alcohol, committed by women, and across different age groups). If the average value of the dependent variable (i.e., the daily crime rate) for all crimes equals the average value of the daily crime rate in a subcategory multiplied by a coefficient k, then the resulting beta estimate for the effect of weather on crime for each individual specification can also be multiplied by this coefficient k.

The second method assumes that the sum of the weather effect estimates for all subgroups of offenses equals the estimate obtained from a regression run on all offenses committed, irrespective of clearance rate. In other words, the beta estimate for crimes committed by men plus the beta estimate for crimes committed by women equals the beta estimate from the regression on all crimes. This approach is similarly applied to other subcategories, such as alcohol consumption and offender age. Given that a 100% clearance rate is unrealistic in real life, I multiply the number of offenses in each subcategory by the inverse of the clearance rate.

The validity of these two approaches is tested as follows. If the right-hand side of the regression equation holds both for all crimes and for the sum of the subgroup-specific regressions, I conclude that there is no significant difference between these subgroups. Otherwise, there is reason to believe that the effect in a given subgroup differs from the effect estimated for all offenses irrespective of clearance rate. I compare the multiplied and adjusted coefficients using a z-test by (Paternoster *et al.* 1998):

$$z = \frac{\beta^1 - \beta^2}{\sqrt{Var(\beta^1) + Var(\beta^2)}}$$

where β^1 and β^2 stand for beta estimators from regressions 1 and 2 and $Var(\cdot)$ denotes the variance.

Thirdly, because the most common interpretation of the coefficient of determination (R-squared or R^2) is how well the regression model explains the dependent variable, I use these statistics to compare different groups. However, one limitation is namely that the R^2 might change because of any independent variables in the regression, not only because of the weather variable.

I use all three methods combined together to interpret the results of each subgroup. Results of these three methods are provided in Table A3.27 and Table A3.28 (first method), Table A3.29 and Table A3.30 (second method) and Table A3.31 (third R^2 method).

(Ranson 2014) suggests using Poisson regression for crime categories where the majority of observations is zero. Since the small number of observations in homicides and sex crimes (see Table 3.2) is also my case, I use Poisson regression for those crime categories. I estimate the remaining crime categories by OLS regression.

3.5 Results

The subsections below discuss the different effects of weather on crime under different specifications. Appendix presents the full regression tables. Table A3.27 and Table A3.28 show the Z-score statistics, while Table A3.29 and Table A3.30 show the regression coefficients, recalculated so that they can be compared with each other. For each criminal activity, I examine the effect of average daily temperature either alone or in combination with total daily precipitation, average daily visibility, and minimum and maximum daily atmospheric pressure. In addition, I also investigate a possible inverse U-shape relationship between crime and temperature. Section 3.6 provides further discussion.

3.5.1 Overall effect

Figure 3.3 and Table A3.1, Table A3.6, Table A3.11, Table A3.16 and Table A3.21 describe the effects of weather on five types of crime rates. Based on the results, I conclude that temperature has a positive significant effect on both violent and property crime rates. In particular, heat increases the total number of assaults, sex crimes, thefts and robberies.

The second specification in Table A3.1, Table A3.6, Table A3.11, Table A3.16 and Table A3.21 test for the presence of a quadratic relationship between outdoor temperature and crime rates. The NAE model by (Bell 1992) expects this quadratic relationship to be concave. Based on my results, for assaults, thefts and robberies the relationship between temperature and crime is concave, as assumed by the NAE model. On the other hand, in my models I detect a simple linear relationship, as proposed by GA model, only for sex crimes.

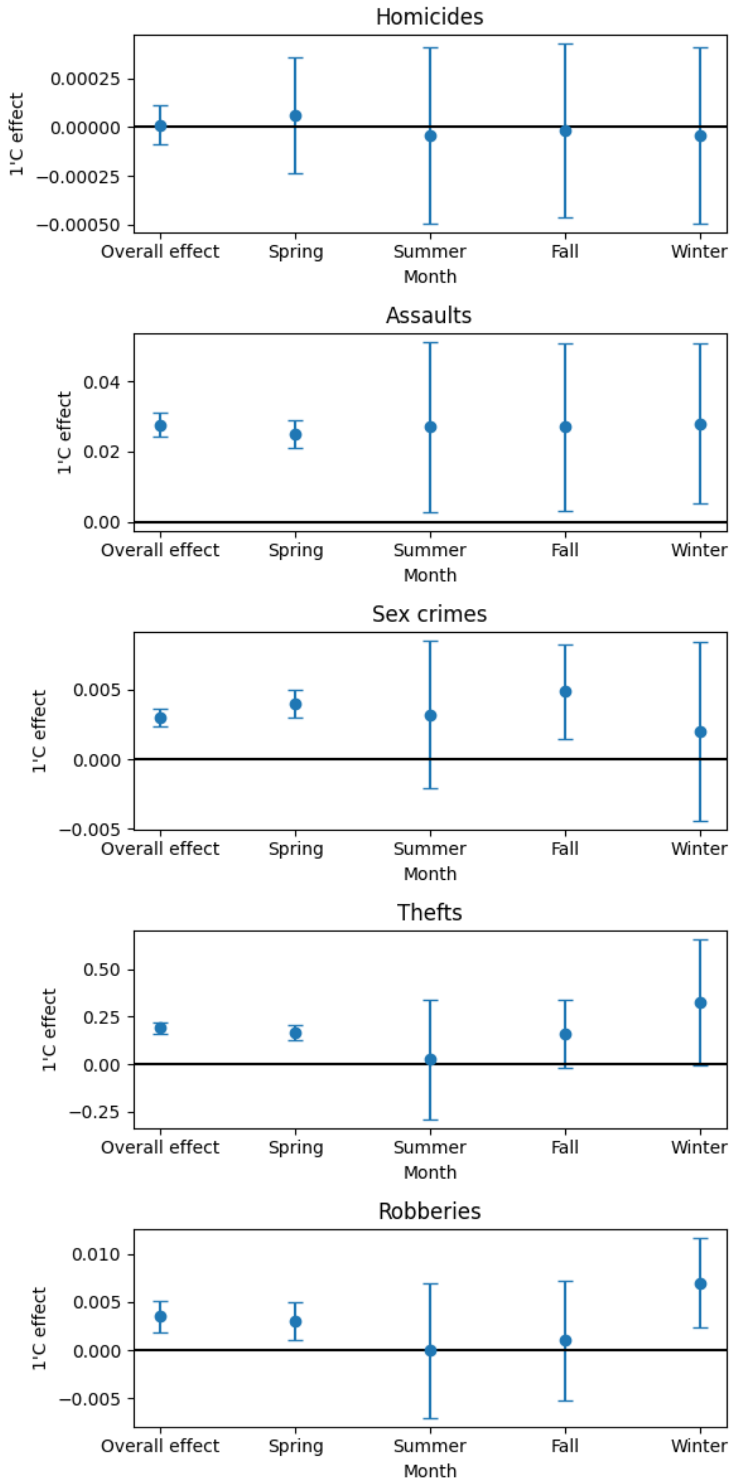
Based on the results, rain has a negative significant effect on rates of assaults and sex crimes. A possible explanation may be in RA theory ((Cohen & Felson 1979)) according to which rain reduces the chances of the offender and the victim meeting each other.

Visibility appears to increase total assault and theft rates. I draw the following conclusions from this result: First, visibility is an important criterion for what is considered good weather, (Won *et al.* 2020). Thus it is possible to deduce that the RA theory by (Cohen & Felson 1979) explains weather-related crime. In other words, nice weather as measured by high daily visibility, increases the chances of criminal and victim meeting together. Secondly, because visibility also impacts property crime rates, it appears that offenders are aware that on days with good weather there is a greater chance for a theft to take place.

3.5.2 Seasonal effect

Table A3.26 and Figure 3.3 decompose temperature effects across seasons of the year. Generally, it appears that the temperature effect is consistent among all seasons of the year. Moreover, the effect of temperature on thefts and robberies appears to be stronger in spring and winter. This result deserves further analysis in a separate research paper. One possible explanation could be that people take time off work in the summer months and spend more time in their summer properties, which reduces the chances of offenders finding these properties unprotected.

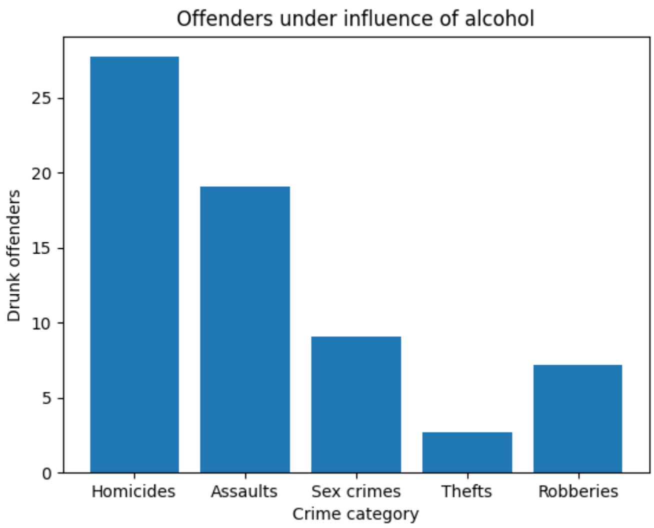
Figure 3.3: Overall effect with seasonal decomposition of the temperature effect on crime categories



3.5.3 Alcohol effect

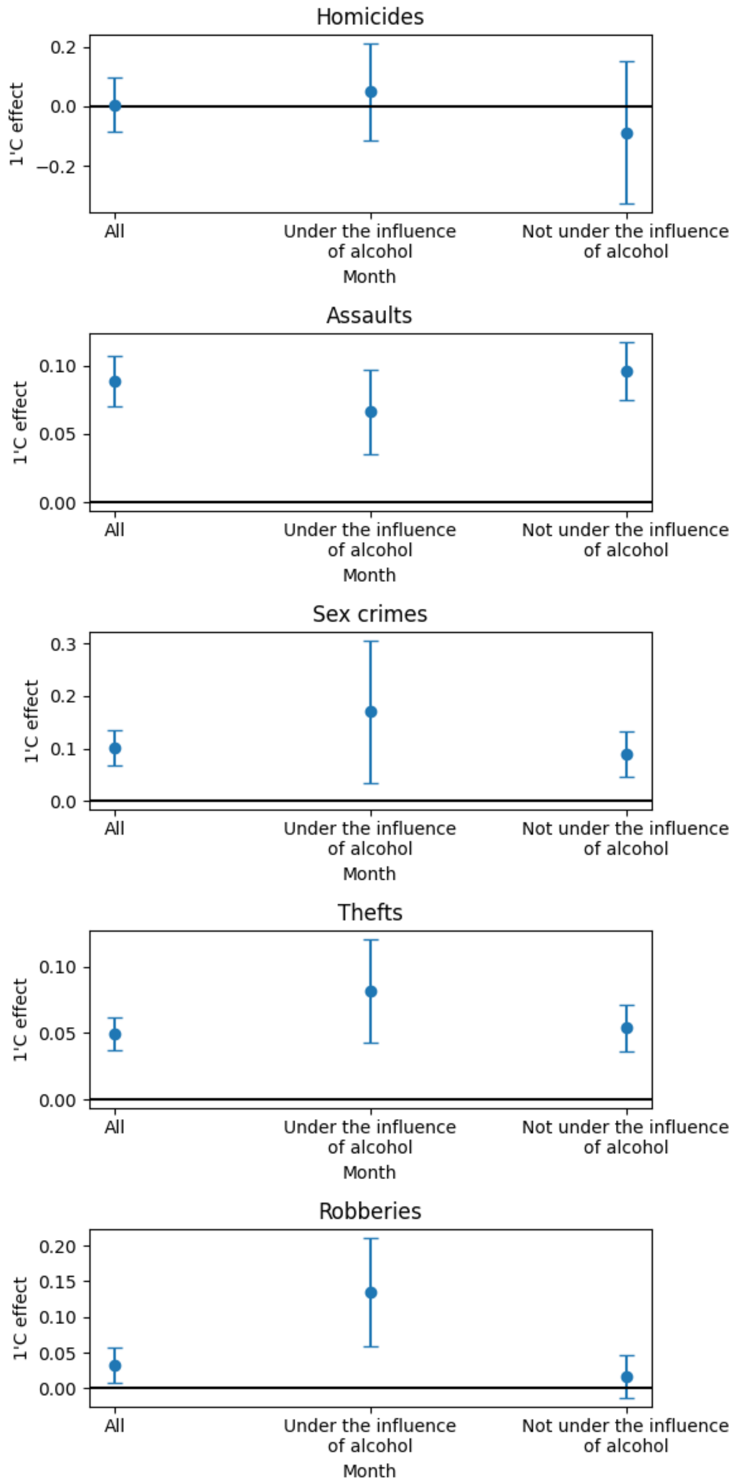
This subsection looks at the impact of weather on crime rates among people under the influence of alcohol and those who are sober. Detailed regression results are in Table A3.2, Table A3.7, Table A3.12, Table A3.17 and Table A3.22. Figure 3.4 shows what percentage of offenders commit crimes under the influence of alcohol. Violent crimes are committed under the influence of alcohol more often than property crimes. Figure 3.5 plots the results[6]. According to the results, the temperature effect on crime rates is stronger for sexual crimes, thefts and robberies for drunk offenders than sober offenders. The opposite effect is observed for drunken offenders of assaults. No special differential effect of precipitation, visibility and air pressure is observed between drunk and sober offenders. For types of crimes that are committed with higher levels of alcohol, I expect higher effects of temperature on the crime and vice versa.

Figure 3.4: Percentage of drunk offenders among crime categories.



[6]Estimates weighted by the inverse mean of committed offenses in the category.

Figure 3.5: Temperature effect on crime per drunk and not drunk offenders.

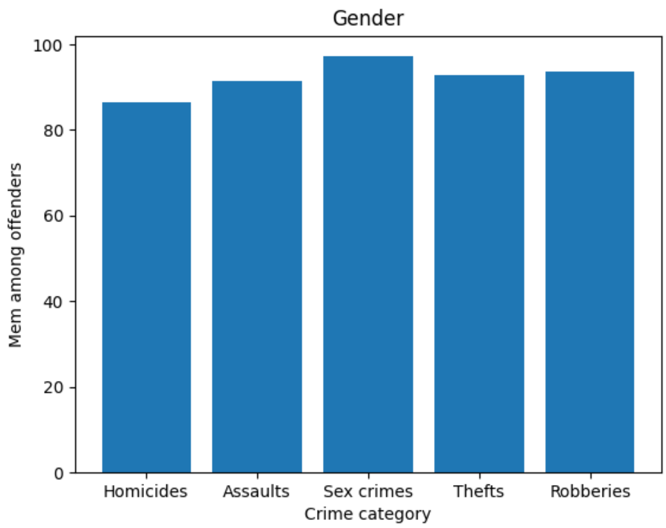


3.5.4 Gender effect

This subsection focuses at the impact of weather on crime rates among offenders gender. The main reason that the gender of the offender might be influential when examining the effect of weather on crime is the Routine Activity model. (Shirazi 2019) argues that men spend more free time doing outdoor activities than women. Moreover, in the Czech Republic, the majority of outdoor work is carried out by men, who are therefore more exposed to outdoor weather, (CZSO 2020). Finally, (Gross 1993) argues that men consume more alcohol than women.

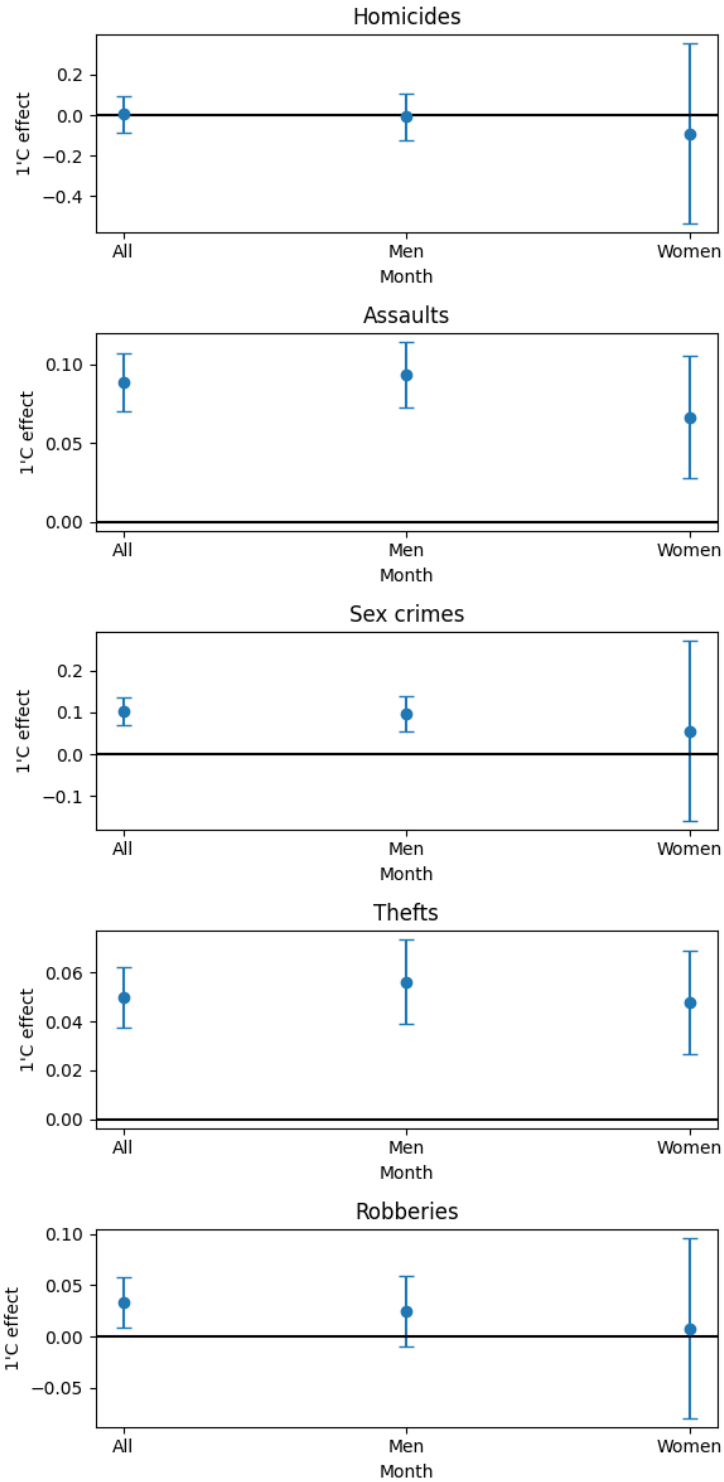
Detailed results are in Table A3.3, Table A3.8, Table A3.13, Table A3.18 and Table A3.23. Figure 3.6 shows what percentage of offenders are men[7]. Based on the results (Figure 3.7), temperature has a stronger impact on crime for male than female offenders for assaults and thefts. No such difference between men and women was noted for other crime categories.

Figure 3.6: Percentage of men offenders among crime categories.



[7]Estimates weighted by the inverse mean of committed offenses in the category.

Figure 3.7: Temperature effect on crime per male and female offenders.



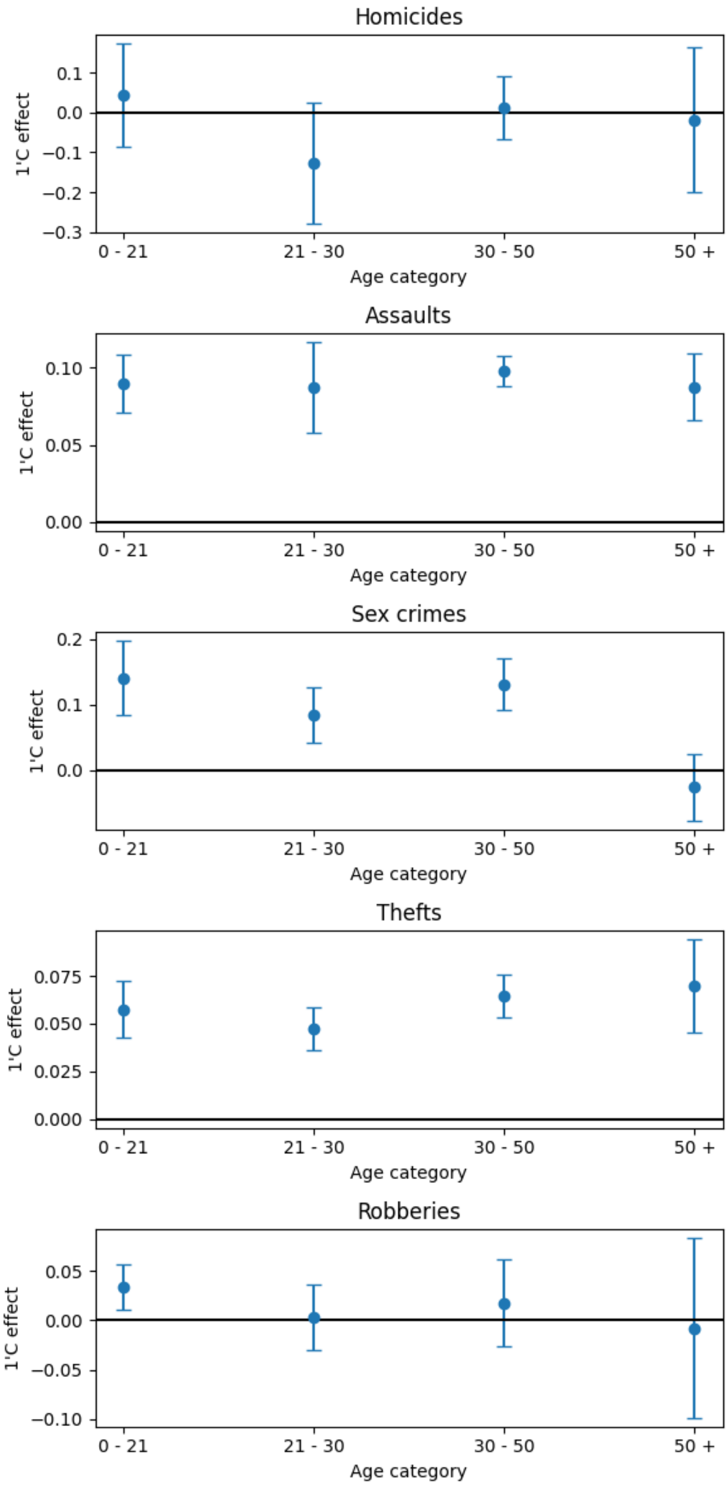
3.5.5 Age effect

The last subsection focuses on heterogeneity in weather effects on crime rates across different age cohorts of offenders. (Shirazi 2019) finds that people spend different amounts of time on outdoor activities across age groups. Similarly, (Shaw *et al.* 2011) argue that the amount of alcohol consumption varies depending on a person's age.

Detailed results are in Table A3.4, Table A3.5, Table A3.9, Table A3.10, Table A3.14, Table A3.15, Table A3.19, Table A3.20, Table A3.24 and Table A3.25. Temperature effects are plotted in Figure 3.8, precipitation effects in Figure A3.2[8]. The only significant decrease in temperature effect on crime is observed for sexual crimes. This decline in offenders over 50 seems to be explained by a general decline in sexual activity in older age groups ((Ueda *et al.* 2020) ; (Nicolosi *et al.* 2004)). The precipitation effect appears to be consistent among all age categories for all crimes.

[8]Estimates weighted by the inverse mean of committed offenses in the category.

Figure 3.8: Age decomposition of the temperature effect on crime categories



3.5.6 Robustness checks

To ensure the robustness of the results, several tests were conducted. First, to check for possible spatial autocorrelation in crime rates between districts, a Moran's I test was performed. As shown in Table A3.32, none of the crime categories suffer from spatial autocorrelation. Second, the crime categories were regressed on an extreme temperature dummy variable, defined as a binary indicator equal to 1 if the daily temperature exceeds the 70th percentile and 0 otherwise. Based on the results in Table A3.33, redefining temperature as a dummy variable does not alter the overall interpretation of the results in the main specification. Third, Table A3.34 provides a more granular view by distinguishing between different percentiles of extreme temperatures. According to the results, assaults increase with higher temperatures, while sex crimes follow an inverted U-shaped pattern—rising at moderate extremes but declining at the hottest temperatures. These findings are consistent with the main specification. To address potential heterogeneity between weekdays and non-working days, the baseline specification is extended by interacting temperature with an indicator for weekends and public holidays (Table A3.35). The results reveal a statistically significant positive interaction between temperature and non-working days, indicating that the effect of temperature on crime is stronger on weekends and holidays. In addition, cumulative heat exposure and temperature anomalies, such as consecutive hot days and weekly temperature maxima, are examined to assess whether aggressive behavior intensifies beyond the temperature level itself, Table A3.35 and Table A3.36. The results indicate that these alternative specifications do not alter the overall interpretation of the baseline findings, remaining consistent with both adaptation-based responses and the General Aggression and Negative Affect Escape frameworks discussed above. Finally, I test whether weather affects police effectiveness rather than underlying criminal behavior using a case-study regression framework in which the dependent variable indicates whether an individual crime was cleared. If higher temperatures increased police activity or effectiveness, this would imply higher clearance rates and raise reverse causality concerns. The results do not support this channel. Estimated temperature effects are generally small, and even where statistically significant, most notably for assaults and thefts, the magnitudes are economically negligible. Moreover, the estimated temperature coefficient is negative, which runs counter to the reverse causality interpretation. Overall, weather-induced changes in police effectiveness are unlikely to drive the main findings (Table A3.37).

3.5.7 Limitations

This study acknowledges several limitations. First, as with all administrative police data, the analysis captures only crimes that were reported to the police, and weather conditions may also affect individuals' willingness to report crimes.

Second, while differences in police effectiveness in investigating offenses do not affect the total number of crimes committed-and thus do not bias the main specification-they may matter for the additional analyses that rely on detected offenses only, such as those distinguishing crimes by age, gender, or alcohol intoxication status.

Third, the crime dataset does not include information on whether crimes occurred indoors or outdoors, nor on how much time victims or offenders spent outside. Likewise, it is not possible to assess the role of indoor conditions (e.g., air conditioning) or outdoor features in shaping exposure to temperature.[9] On the other hand, high outdoor temperature clearly may affect indoor crime, particularly in the Czech Republic where air conditioning is uncommon, Šimek *et al.* (2019). [10]

Finally, while the analysis controls for temperature, precipitation, visibility, and air pressure, not all environmental variables, most notably air pollution, can be accounted for.

Despite these limitations, the study provides valuable evidence on short-term weather–crime relationships in a developed country context, where such research remains scarce.

3.6 Discussion

This section summarizes results from all regressions and assesses which of the theories describing the relationship between weather and aggression (as

[9]See Jonescu *et al.* (2024), who emphasize that both micro- and macro-climatic factors-such as urban heat islands, population density, and green canopy cover—can influence criminal behavior through their effects on thermal comfort and urban design.

[10]Humidity data are also not available in the OpenWeather API source. However, since the Czech Republic is a landlocked country with generally moderate humidity levels, this omission is unlikely to substantially bias the results.

discussed in the Section 3.1) is the most plausible. Table 3.5 shows for which subcategories of crime (gender, alcohol, age) there is a linear relationship between temperature (as proposed by the GA model by (Anderson & Anderson 1998) and (Rotton & Cohn 2000)) and crime, and for which there is a quadratic relationship (as suggested by the NAE model by (Bell 1992)).

To summarize the GA vs NAE model results, I conclude that neither one of these theories is applicable for homicide rates. In other words, temperature has no effect on murders. This result is not surprising, as according to a meta-analysis by (Mišák 2024) most studies that found a significant relationship between heat and murders suffer from a publication bias.

The GA model appears to hold for all specifications of assaults. Because assaults are the most commonly committed violent crime (see Table 3.2), and also because scholars such as (Chersich *et al.* 2019) attribute violent crimes caused by the rise in temperature to psychological factors (especially greater aggression, emotional discomfort) and by physiological factors (e.g. dehydration), it is not surprising that heat causes a significant increase in assault rates. Moreover, I detected a non-linear relationship between temperature and assault rates, as proposed by NAE model, for all committed assault rates together, for male offenders and for offenders under 21. One possible explanation may be that men are more likely to work outdoors and are therefore more exposed to outdoor temperatures, (Hraba *et al.* 1996). Similar reasoning can be applied to explain the non-linear relationship for the youngest group of assault offenders - young people spend the most time outdoors among all age groups.

I find a linear trend between temperature and sexual crimes except for women offenders and offenders above 50 years old. This finding appears to be explained by the fact that almost no women commit sexual crimes (see Figure 3.6) and the general decline in sexual activity among people over 50 (see Subsection 3.5.5). No result supporting the non-linear relationship between temperature and sexual crimes, as suggested by the NAE model, was found for any specification.

I identify both a linear and concave link between temperature for all subgroups of thefts. In other words, the heat effect on theft rates appears to be explainable by both the GA and NAE models. According to (Horrocks & Menclova 2011), results from existing studies differ on whether the temperature increases property crimes. My results are in the line with those studies that say yes. Moreover, I find that the temperature effect on thefts appears to be stronger for men than women.

Finally, I find a linear trend between temperate and robbery rates for all committed robberies, drunk offenders and offenders under 21. Moreover, the NAE model describes the relationship between temperature and robbery rates for all robberies together and for the youngest group of offenders. The reasoning seems to be the same as in the case of assaults - these groups of offenders spend the most time outdoors.

The interaction results with non-working days, defined as weekends and public holidays, indicate that temperature effects on crime are generally stronger when regular work routines are suspended, Table A3.35. Specifically, positive and statistically significant interaction terms are observed for assaults, sex crimes, thefts, and robberies, whereas no corresponding interaction effect is found for homicides, consistent with a routine-activity mechanism driven by increased social interaction and exposure.

Overall, the results suggest that no single theoretical framework can fully explain the weather–crime relationship. The linear effects observed for most crime types are consistent with the General Affect (GA) model, which links rising temperature to aggression through psychological discomfort. However, the concave relationship between temperature and crime rates found for assaults, thefts, and robberies supports the Negative Affect Escape (NAE) model, implying that beyond a certain threshold, extreme heat suppresses crime. Finally, the mediating roles of alcohol in sexual crimes, thefts and robberies align with the Routine Activity (RA) model, emphasizing the role of alcohol consumption as a key factor influencing the temperature–crime relationship.

Table 3.5: Crime categories statistics

		All	**Alcohol**		**Gender**		**Age**			
			Drunk	Non drunk	Men	Women	0-21	21-30	30-50	50+
Homicides	Linear	N	N	N	N	N	N	N	N	N
	Non-linear	N	N	N	N	N	N	N	N	N
Assaults	Linear	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Non-linear	Y	N	N	Y	N	Y	N	N	N
Sex crimes	Linear	Y	Y	Y	Y	N	Y	Y	Y	N
	Non-linear	N	N	N	N	N	N	N	N	N
Thefts	Linear	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Non-linear	Y	Y	Y	Y	Y	Y	Y	Y	Y
Robberies	Linear	Y	Y	N	N	N	Y	N	N	N
	Non-linear	Y	N	N	N	N	Y	N	N	N

Note: Summary of linear and non-linear (concave) relationships between temperature and crime. Y = yes, N = no.

3.7 Conclusion

Using daily panel data from the Czech Republic, this paper analyzes the impact of weather on various types of crimes, namely homicides, assaults, sexual crimes, thefts, and robberies. The study specifically investigates the mechanisms through which weather influences crime rates. I empirically test established weather-crime hypotheses, such as the General Affect model, Negative Affect Escape model, and Routine Activity model, while also considering alcohol consumption as a potential mechanism, and gender and age as sources of heterogeneity in offenders' responses to weather.

According to the results, alcohol appears to be the main reason why higher temperature causes higher crime rates for sexual crimes, thefts and robberies. Given the fact that the World Health Organization ((WHO 2019)) considers alcohol a major cause of violence and crime, these findings seem to be policy relevant. Moreover, I find that temperature has a stronger effect on male than female offenders for assault rates and theft rates, which is possible to explain by the Routine Activity theory. The temperature's effect on crime rates appears to be consistent among all age groups, except for sexual crimes, where I detect no temperature-related effect for offenders above 50.

I use other weather variables, such as precipitation, visibility and air pressure to analyze whether these factors also affect crime. Rain seems to decrease the number of assaults and sexual crimes committed, which may be explained by the Routine Activity model, i.e., that on rainy days people limit their interactions with each other. Furthermore, based on the results, I argue that better visibility increases assaults and thefts. Finally, I find no conclusive result on the effect of air pressure on any of the crime categories studied.

Appendix

Homicides

Table A3.1: Homicides - All crimes

Variable	All	All	All	All
$Temperature$	0.00001	-0.00013	0.000009	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Temperature^2$		0.000009		
		(0.000006)		
$Rain$			-0.00007	
			(0.0001)	
$Visibility$				0.0000004
				(0.0000005)
$Max\,pressure$				-0.00016
				(0.0003)
$Min\,pressure$				0.00018
				(0.00019)
Intercept	0.0122*	0.0113	0.0121*	0.007
	(0.007)	(0.007)	(0.007)	(0.089)
N	584,000	584,000	584,000	584,000
Pseudo R^2	0.001	0.001	0.001	0.001

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of homicides per 1.000.000 population.

Table A3.2: Homicides - Alcohol effects

Variable	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**
Temperature	0.00003	-0.00006	0.00006	-0.00019*	0.000028	-0.00006	0.00004	0.00019*
	(0.00006)	(0.0001)	(0.00006)	(0.0001)	(0.00006)	(0.0001)	(0.00007)	(0.0001)
Temperature^2			-0.000002	0.000008				
			(0.000003)	(0.000005)				
Rain					-0.00006***	-0.0001***		
					(0.00002)	(0.00004)		
Visibility							-0.0000001	0.0000002
							(0.00005)	(0.0000004)
Max pressure							-0.00006	-0.000005
							(0.00007)	(0.00017)
Min pressure							0.00004	0.00007
							(0.00005)	(0.0001)
Intercept	0.00314	0.0096*	0.00332	0.0088*	0.00313	0.0096*	0.0213	-0.0396
	(0.0024)	(0.005)	(0.00238)	(0.0049)	(0.00244)	(0.005)	(0.0259)	(0.056)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of homicides per 1.000.000 population.

Table A3.3: Homicides - Gender effects

Variable	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
$Temperature$	-0.00001	-0.00002	-0.00005	-0.0001	-0.00001	-0.00002	0.0002*	-0.00002
	(0.0001)	(0.00006)	(0.0001)	(0.0001)	(0.00009)	(0.00006)	(0.0001)	(0.00003)
$Temperature^2$			0.000003	0.000005				
			(0.000005)	(0.000004)				
$Rain$					-0.0001***	-0.00003		
					(0.00004)	(0.00002)		
$Visibility$							0.0000003	0.00000001
							(0.0000005)	(0.00000007)
$Max\,pressure$							-0.0002	0.00002
							(0.0002)	(0.00006)
$Min\,pressure$							0.0002	-0.00003
							(0.0002)	(0.00005)
Intercept	0.012*	0.0008	0.0116*	0.0004	0.0119*	0.0008	0.018	0.01
	(0.007)	(0.0005)	(0.007)	(0.0007)	(0.007)	(0.0005)	(0.08)	(0.019)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of homicides per 1.000.000 population.

Table A3.4: Homicides - Age effects

Variable	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**
Temperature	0.00001	-0.00002	0.00001	0.00003	-0.00005	-0.0001	-0.00005	0.00002
	(0.00003)	(0.00004)	(0.00003)	(0.00003)	(0.00006)	(0.00008)	(0.00006)	(0.00006)
Temperature^2		0.000002	0.000005					
		(0.000002)				(0.000004)		
Rain			-0.00003**				-0.00004	
			(0.00001)				(0.00003)	
Visibility				0.0000**				0.0000003
				(0.0000)				(0.0000003)
Max pressure				0.00002				0.00005
				(0.00005)				(0.00008)
Min pressure				-0.00001				-0.00004
				(0.00005)				(0.00008)
Intercept	0.003	0.003	0.003	-0.016	0.0036	0.003	0.004	0.008
	(0.003)	(0.003)	(0.003)	(0.012)	(0.002)	(0.002)	(0.002)	(0.029)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of homicides per 1.000.000 population.

Table A3.5: Homicides - Age effects

Variable	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**
Temperature	0.00001	0.00004	0.00001	0.0001	-0.000005	-0.00004	-0.000006	0.00002
	(0.00006)	(0.00008)	(0.00006)	(0.00007)	(0.00005)	(0.00006)	(0.00005)	(0.00004)
Temperature^2		-0.000002				0.000002		
		(0.000004)				(0.000002)		
Rain			-0.00009**				-0.00002**	
			(0.00003)				(0.000007)	
Visibility				-0.00000002				-0.00000005
				(0.0000002)				(0.00000005)
Max pressure				-0.0002				-0.00007
				(0.0002)				(0.00007)
Min pressure				0.0002				0.00004
				(0.0001)				(0.00005)
Intercept	0.004*	0.005*	0.004*	-0.004	0.002***	0.014***	0.002***	0.04
	(0.002)	(0.002)	(0.002)	(0.05)	(0.0004)	(0.0004)	(0.0004)	(0.04)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of homicides per 1.000.000 population.

Assaults

Table A3.6: Assaults - All crimes

Variable	All	All	All	All
$Temperature$	0.0277***	0.0323***	0.0276***	0.0228***
	(0.00348)	(0.0045)	(0.0035)	(0.005)
$Temperature^2$		-0.0003*		
		(0.0001)		
$Rain$			-0.011**	
			(0.0048)	
$Visibility$				0.000035**
				(0.00001)
$Max\,pressure$				-0.004
				(0.0038)
$Min\,pressure$				0.006*
				(0.003)
Intercept	3.1442***	3.171***	3.143***	-0.026
	(0.325)	(0.33)	(0.325)	(1.76)
N	584,000	584,000	584,000	584,000
R^2	0.126	0.126	0.126	0.126

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of assaults per 1.000.000 population.

Table A3.7: Assaults - Alcohol effects

Variable	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**
Temperature	0.00315***	0.0184***	0.00411***	0.0213***	0.00312***	0.0184***	0.0026***	0.0139***
	(0.0009)	(0.0025)	(0.0012)	(0.0031)	(0.0009)	(0.0025)	(0.0008)	(0.0037)
$Temperature^2$			-0.00006	-0.0002				
			(0.000048)	(0.00012)				
Rain					-0.00252	-0.0059		
					(0.0018)	(0.0039)		
Visibility							0.000005*	0.00002**
							(0.000003)	(0.000008)
Max pressure							0.0003	-0.004
							(0.0014)	(0.0028)
Min pressure							0.0003	0.0055**
							(0.0015)	(0.0023)
Intercept	0.527***	2.1608***	0.533***	2.177***	0.527***	2.16***	-0.46	-0.159
	(0.083)	(0.307)	(0.083)	(0.310)	(0.083)	(0.307)	(0.759)	(1.5)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.04	0.084	0.04	0.084	0.04	0.084	0.04	0.084

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of assaults per 1.000.000 population.

Table A3.8: Assaults - Gender effects

Variable	Men	Women	Men	Women	Men	Women	Men	Women
$Temperature$	0.021***	0.0014***	0.026***	0.001	0.021***	0.0014***	0.017***	0.001**
	(0.00283)	(0.0005)	(0.0037)	(0.0007)	(0.0028)	(0.0005)	(0.004)	(0.0005)
$Temperature^2$			-0.00003**	0.00003				
			(0.00013)	(0.00003)				
$Rain$					-0.0079*	-0.0012*		
					(0.004)	(0.0007)		
$Visibility$							0.00002**	0.000002
							(0.000001)	(0.000002)
$Max\,pressure$							-0.0025	-0.0009
							(0.003)	(0.0008)
$Min\,pressure$							0.005*	0.0009
							(0.0026)	(0.0007)
Intercept	2.579***	0.155***	2.605***	0.153***	2.578***	0.155***	-1.07	0.045
	(0.321)	(0.029)	(0.325)	(0.029)	(0.321)	(0.029)	(1.33)	(0.378)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.101	0.014	0.101	0.014	0.101	0.014	0.101	0.014

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of assaults per 1.000.000 population.

Table A3.9: Assaults - Age effects

Variable	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**
$Temperature$	0.0047***	0.0077***	0.005***	0.004**	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.0016)	(0.001)	(0.0016)	(0.001)	(0.002)	(0.001)	(0.001)
$Temperature^2$		-0.0002**				-0.00004		
		(0.00007)				(0.00006)		
$Rain$			0.0004				-0.003	
			(0.002)				(0.002)	
$Visibility$				0.000004				0.000009*
				(0.000003)				(0.000005)
$Max\,pressure$				-0.0001				-0.002
				(0.0013)				(0.001)
$Min\,pressure$				0.001				0.003**
				(0.001)				(0.001)
Intercept	0.88***	0.898***	0.88***	-0.816	0.702***	0.706***	0.702***	0.004
	(0.291)	(0.295)	(0.07)	(0.67)	(0.071)	(0.072)	(0.071)	(0.656)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.027	0.027	0.027	0.027	0.040	0.040	0.040	0.040

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of assaults per 1.000.000 population.

Table A3.10: Assaults - Age effects

Variable	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**
Temperature	0.01***	0.01***	0.01***	0.007***	0.002***	0.003***	0.002***	0.002**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.0005)	(0.0006)	(0.0005)	(0.0008)
$Temperature^2$		-0.0000009				-0.00002		
		(0.00006)				(0.00003)		
Rain			-0.005**				-0.002**	
			(0.002)				(0.0008)	
Visibility				0.00001**				0.000004**
				(0.000004)				(0.000002)
Max pressure				0.0002				-0.001
				(0.002)				(0.001)
Min pressure				0.0008				0.001
				(0.002)				(0.001)
Intercept	0.999***	0.999***	0.999***	-0.432	0.153***	0.155***	0.152***	0.223
	(0.105)	(0.105)	(0.105)	(0.946)	(0.029)	(0.029)	(0.029)	(0.399)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.065	0.065	0.065	0.065	0.017	0.017	0.017	0.017

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of assaults per 1.000.000 population.

Sex crimes

Table A3.11: Sex crimes - All crimes

Variable	All	All	All	All
$Temperature$	0.0030***	0.0034***	0.003***	0.0036***
	(0.0006)	(0.0008)	(0.0006)	(0.0009)
$Temperature^2$		-0.00003		
		(0.00003)		
$Rain$			-0.0028***	
			(0.0009)	
$Visibility$				0.000002
				(0.000002)
$Max\,pressure$				-0.0003
				(0.0006)
$Min\,pressure$				0.00057
				(0.0006)
Intercept	0.155***	0.157***	0.154***	0.219
	(0.0387)	(0.0392)	(0.039)	(0.421)
N	584,000	584,000	584,000	584,000
Pseudo R^2	0.018	0.018	0.018	0.018

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of sex crimes per 1.000.000 population.

Table A3.12: Sex crimes - Alcohol effects

Variable	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**
Temperature	0.00037**	0.00167***	0.0003	0.0023***	0.00037**	0.0016***	0.0007***	0.0016**
	(0.00018)	(0.0005)	(0.00018)	(0.00067)	(0.00018)	(0.0005)	(0.0002)	(0.0007)
Temperature^2			0.000005	-0.00004				
			(0.000009)	(0.00003)				
Rain					-0.00027	-0.0018**		
					(0.00017)	(0.0008)		
Visibility							0.00000001	0.000002
							(0.0000004)	(0.000001)
Max pressure							-0.000001	-0.0004
							(0.00013)	(0.0005)
Min pressure							-0.00001	0.00065
							(0.0001)	(0.00049)
Intercept	0.0386*	0.068**	0.0381*	0.072**	0.0385*	0.068**	0.123	0.077
	(0.0217)	(0.028)	(0.0219)	(0.028)	(0.0217)	(0.028)	(0.144)	0.146
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.022	0.013	0.022	0.013	0.022	0.013	0.022	0.013

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of sex crimes per 1.000.000 population.

Table A3.13: Sex crimes - Gender effects

Variable	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Temperature	0.002***	0.00003	0.0027***	0.0001*	0.002***	0.00003	0.0023***	0.0001
	(0.00054)	(0.00007)	(0.0007)	(0.00008)	(0.0005)	(0.00007)	(0.0007)	(0.0001)
Temperature^2			-0.00004	-0.000007				
			(0.00003)	(0.000004)				
Rain					-0.002**	0.000007		
					(0.0005)	(0.0001)		
Visibility							0.000002	-0.0000001
							(0.000002)	(0.0000002)
Max pressure							-0.0002	-0.0002*
							(0.0006)	(0.0001)
Min pressure							0.0004	0.0001*
							(0.0006)	(0.00007)
Intercept	0.12***	-0.0015**	0.125***	-0.0009	0.12***	-0.0015**	0.198	0.087
	(0.0385)	(0.0008)	(0.0391)	(0.0009)	(0.039)	(0.0008)	(0.429)	(0.058)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.014	0.001	0.014	0.001	0.014	0.001	0.014	0.001

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of sex crimes per 1.000.000 population.

Table A3.14: Sex crimes - Age effects

Variable	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**
$Temperature$	0.001***	0.0015***	0.0011***	0.0009**	0.0004*	0.0002	0.0004*	0.0006**
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
$Temperature^2$		-0.00002				0.00001		
		(0.00002)				(0.00001)		
$Rain$			-0.0002				-0.0006	
			(0.0006)				(0.0004)	
$Visibility$				0.000001				0.0000007
				(0.000001)				(0.0000006)
$Max\,pressure$				-0.0003				0.0003
				(0.0004)				(0.0003)
$Min\,pressure$				0.0003				-0.0003
				(0.0004)				(0.0003)
Intercept	0.054**	0.056**	0.05**	0.379	0.031	0.03	0.03	0.01
	(0.025)	(0.026)	(0.025)	(0.283)	(0.02)	(0.02)	(0.02)	(0.02)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.006	0.006	0.006	0.006	0.005	0.005	0.005	0.005

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of sex crimes per 1.000.000 population.

Table A3.15: Sex crimes - Age effects

Variable	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**
Temperature	0.001*	0.001**	0.001*	0.0007*	-0.00005	0.0002	-0.00005	0.0002
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Temperature^2		-0.00002				-0.00002		
		(0.0002)				(0.000009)		
Rain			-0.001***				-0.00006	
			(0.0003)				(0.0003)	
Visibility				-0.0000002				0.0000005
				(0.0000007)				(0.0000003)
Max pressure				-0.0003				-0.00008
				(0.0004)				(0.0002)
Min pressure				0.0004				0.0002
				(0.0004)				(0.0002)
Intercept	0.033*	0.036**	0.033*	-0.048	0.0005	0.002	0.0005	-0.06
	(0.017)	(0.02)	(0.017)	(0.148)	(0.006)	(0.006)	(0.006)	(0.114)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.006	0.006	0.006	0.006	0.002	0.002	0.002	0.002

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of sex crimes per 1.000.000 population.

Thefts

Table A3.16: Thefts - All crimes

Variable	All	All	All	All
$Temperature$	0.191***	0.317***	0.191***	0.162***
	(0.0287)	(0.035)	(0.029)	(0.037)
$Temperature^2$		-0.008***		
		(0.001)		
$Rain$			0.0379	
			(0.03)	
$Visibility$				0.0004***
				(0.0002)
$Max\,pressure$				-0.16***
				(0.052)
$Min\,pressure$				0.128***
				(0.039)
Intercept	76.275***	77.02***	76.278***	95.89***
	(3.38)	(3.47)	(3.38)	(16.2)
N	584,000	584,000	584,000	584,000
R^2	0.410	0.410	0.410	0.410

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of thefts per 1.000.000 population.

Table A3.17: Thefts - Alcohol effects

Variable	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**	**Alcohol**	**No Alcohol**
Temperature	0.00240***	0.0575***	0.0043***	0.106***	0.0024***	0.0574***	0.0007***	0.048***
	(0.0007)	(0.0114)	(0.00127)	(0.0162)	(0.0007)	(0.0114)	(0.0002)	(0.0159)
Temperature^2			-0.00012**	-0.0031***				
			(0.00005)	(0.0005)				
Rain					0.0009	-0.0038		
					(0.0017)	(0.012)		
Visibility							0.00000001	0.0001**
							(0.0000004)	(0.00004)
Max pressure							-0.000001	-0.0233*
							(0.0001)	(0.0126)
Min pressure							-0.00001	0.0237**
							(0.0001)	(0.011)
Intercept	0.5297***	17.606***	0.541***	17.89***	0.53***	17.605***	0.123	16.826***
	(0.116)	(1.49)	(0.118)	(1.51)	(0.116)	(1.49)	(0.144)	(6.11)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.022	0.208	0.022	0.208	0.022	0.208	0.022	0.208

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of thefts per 1.000.000 population.

Table A3.18: Thefts - Gender effects

Variable	Men	Women	Men	Women	Men	Women	Men	Women
Temperature	0.0585***	0.0037***	0.1076***	0.0006***	0.058***	0.0037***	0.046***	0.0047***
	(0.011)	(0.001)	(0.0159)	(0.001)	(0.011)	(0.001)	(0.0154)	(0.001)
Temperature^2			-0.0031***	-0.0002***				
			(0.0005)	(0.00006)				
Rain					-0.0057	0.0005		
					(0.011)	(0.002)		
Visibility							0.0001**	0.000006
							(0.00004)	(0.000004)
Max pressure							-0.022*	0.0003
							(0.012)	(0.002)
Min pressure							0.022**	0.0006
							(0.011)	(0.002)
Intercept	17.022***	1.564***	17.31***	1.579***	17.022***	1.565***	17.94***	0.191
	(1.5)	(0.098)	(1.52)	(0.099)	(1.5)	(0.078)	(6.53)	(0.854)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.210	0.036	0.210	0.036	0.210	0.036	0.210	0.036

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of thefts per 1.000.000 population.

Table A3.19: Thefts - Age effects

Variable	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**
Temperature	0.027***	0.056***	0.026***	0.02***	0.017***	0.029***	0.017***	0.018***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.004)	(0.006)	(0.004)	(0.007)
$Temperature^2$		-0.0019***				-0.0008***		
		(0.009)				(0.0002)		
Rain			-0.01				0.002	
			(0.07)				(0.006)	
Visibility				0.00005**				0.00004**
				(0.00002)				(0.00002)
Max pressure				-0.009				-0.006
				(0.007)				(0.005)
Min pressure				0.012**				0.006
				(0.006)				(0.004)
Intercept	7.926***	8.098***	7.925***	7.38	5.554***	5.625***	5.554***	4.68*
	(1.07)	(1.08)	(1.07)	(4.7)	(0.404)	(0.412)	(0.404)	(2.37)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.136	0.136	0.136	0.136	0.123	0.123	0.123	0.123

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of thefts per 1.000.000 population.

Table A3.20: Thefts - Age effects

Variable	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**
Temperature	0.017***	0.025***	0.017***	0.012***	0.002***	0.003***	0.002***	0.002**
	(0.003)	(0.004)	(0.003)	(0.004)	(0.0007)	(0.001)	(0.0007)	(0.0007)
Temperature^2		-0.0006***				-0.00009**		
		(0.0001)				(0.00005)		
Rain			0.001				0.001	
			(0.006)				(0.001)	
Visibility				0.00003**				0.000004*
				(0.00001)				(0.000002)
Max pressure				-0.008*				0.0009
				(0.004)				(0.001)
Min pressure				0.006				-0.0006
				(0.004)				(0.001)
Intercept	4.759***	4.81***	4.759***	6.16***	0.348***	0.357***	0.348***	-0.09
	(0.356)	(0.359)	(0.356)	(2.17)	(0.054)	(0.054)	(0.054)	(0.451)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
Pseudo R^2	0.092	0.092	0.092	0.092	0.018	0.018	0.018	0.018

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of thefts per 1.000.000 population.

Robberies

Table A3.21: Robberies - All crimes

Variable	**All**	**All**	**All**	**All**
$Temperature$	0.0035**	0.0066**	0.0034**	0.005*
	(0.0016)	(0.0025)	(0.0016)	(0.0027)
$Temperature^2$		-0.0002**		
		(0.00008)		
$Rain$			-0.0026	
			(0.0022)	
$Visibility$				0.00001*
				(0.000006)
$Max\,pressure$				0.0032
				(0.0023)
$Min\,pressure$				-0.0038*
				(0.002)
Intercept	1.789***	1.808***	1.789***	2.34**
	(0.114)	(0.115)	(0.114)	(1.12)
N	584,000	584,000	584,000	584,000
R^2	0.058	0.058	0.058	0.058

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of robberies per 1.000.000 population.

Table A3.22: Robberies - Alcohol effects

Variable	Alcohol	No Alcohol	Alcohol	No Alcohol	Alcohol	No Alcohol	Alcohol	No Alcohol
Temperature	0.00058**	0.0009	0.00098**	0.0025	0.0006**	0.0009	0.0006	0.0015
	(0.0002)	(0.001)	(0.00038)	(0.002)	(0.00024)	(0.0012)	(0.00048)	(0.0017)
Temperature^2			-0.00003	-0.0001				
			(0.00002)	(0.00007)				
Rain					-0.0003	-0.0036**		
					(0.0004)	(0.0016)		
Visibility							0.0000002	0.000005
							(0.0000008)	(0.000004)
Max pressure							0.00047	0.002
							(0.00037)	(0.0018)
Min pressure							-0.00039	-0.0032*
							(0.00036)	(0.0017)
Intercept	0.0603***	0.8325***	0.0626***	0.842***	0.0603***	0.832***	-0.0365	2.00*
	(0.021)	(0.0981)	(0.0205)	(0.099)	(0.0205)	(0.098)	(0.106)	(1.16)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.004	0.025	0.004	0.025	0.004	0.025	0.004	0.025

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of robberies per 1.000.000 population.

Table A3.23: Robberies - Gender effects

Variable	Men	Women	Men	Women	Men	Women	Men	Women
Temperature	0.0014	0.00003	0.0032	0.0002	0.0014	0.00003	0.0021	0.0004
	(0.0012)	(0.0002)	(0.002)	(0.0003)	(0.001)	(0.0003)	(0.0017)	(0.0003)
$Temperature^2$			-0.0001	-0.00001				
			(0.00007)	(0.00001)				
Rain					-0.004**	-0.00006		
					(0.0016)	(0.0003)		
Visibility							0.000006*	0.0000002
							(0.000003)	(0.000001)
Max pressure							0.0027	-0.0001
							(0.002)	(0.0003)
Min pressure							-0.0039**	0.00002
							(0.0018)	(0.0002)
Intercept	0.843***	0.046***	0.853***	0.047***	0.843***	0.046***	2.1*	0.042
	(0.093)	(0.013)	(0.095)	(0.014)	(0.093)	(0.013)	(1.19)	(0.13)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.025	0.004	0.025	0.004	0.025	0.004	0.025	0.004

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of robberies per 1.000.000 population.

Table A3.24: Robberies - Age effects

Variable	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(0 ; 21]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**	**(21 ; 30]**
Temperature	0.001*	0.0032***	0.001	0.002	0.00006	0.0002	0.00004	0.00003
	(0.0007)	(0.001)	(0.0007)	(0.001)	(0.0006)	(0.0008)	(0.0006)	(0.0007)
Temperature^2		-0.0001***				-0.000006		
		(0.00004)				(0.00003)		
Rain			-0.002				-0.0009	
			(0.001)				(0.0006)	
Visibility				0.000002				0.000004*
				(0.000002)				(0.000002)
Max pressure				0.001				0.0007
				(0.001)				(0.001)
Min pressure				-0.002				-0.001
				(0.001)				(0.0009)
Intercept	0.326***	0.338***	0.325***	0.914	0.293***	0.294***	0.293***	0.887*
	(0.07)	(0.072)	(0.07)	(0.826)	(0.04)	(0.04)	(0.04)	(0.451)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.017	0.017	0.017	0.017	0.010	0.010	0.010	0.010

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of robberies per 1.000.000 population.

Table A3.25: Robberies - Age effects

Variable	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(30 ; 50]**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**	**(50 ; ∞)**
Temperature	0.0002	0.00004	0.0002	0.0008	-0.000007	-0.0001	-0.000007	0.00008
	(0.0005)	(0.0008)	(0.0005)	(0.0007)	(0.00008)	(0.0001)	(0.00008)	(0.0001)
$Temperature^2$		0.00001				0.000006		
		(0.00003)				(0.000005)		
Rain			-0.002***				0.000003	
			(0.0003)				(0.0002)	
Visibility				0.00000002				-0.000000006
				(0.000001)				(0.0000003)
Max pressure				0.0005				0.0003
				(0.0007)				(0.0002)
Min pressure				-0.0007				-0.0004
				(0.0006)				(0.0003)
Intercept	0.244***	0.243***	0.244***	0.287	0.026***	0.026***	0.026***	0.057
	(0.034)	(0.034)	(0.034)	(0.292)	(0.009)	(0.009)	(0.009)	(0.07)
N	584,000	584,000	584,000	584,000	584,000	584,000	584,000	584,000
R^2	0.007	0.007	0.007	0.007	0.001	0.001	0.001	0.001

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of robberies per 1.000.000 population.

Seasonal effects

Table A3.26: Seasonal effects of crime

Variable	Homicides	Assaults	Sex crimes	Thefts	Robberies
$Temperature$	0.00006	0.025***	0.004***	0.167***	0.003*
	(0.0003)	(0.004)	(0.001)	(0.037)	(0.002)
$Summer \cdot Temperature$	-0.0001	0.002	-0.0008	-0.142***	-0.003
	(0.0003)	(0.006)	(0.002)	(0.029)	(0.003)
$Fall \cdot Temperature$	-0.00008	0.002	0.0009	-0.006	-0.002
	(0.0003)	(0.005)	(0.001)	(0.029)	(0.003)
$Winter \cdot Temperature$	-0.0001	0.003	-0.002	0.158***	0.004
	(0.0003)	(0.005)	(0.002)	(0.039)	(0.004)
Intercept	0.01	3.169***	0.162***	77.487***	1.807***
	(0.008)	(0.339)	(0.043)	(3.54)	(0.123)
N	584,000	584,000	584,000	584,000	584,000
(Pseudo) R^2	0.001	0.126	0.018	0.410	0.058

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on a district level. The dependent variable is the number of crimes per 1.000.000 population.

Tests

Table A3.27: Alcohol effect: z-score results.

	All - Alcohol	All - No Alcohol	Alcohol - No Alcohol
Homicides	-0.68	1.19	2.12**
Assaults	1.95**	-0.54	-3.51***
Sex crimes	-3.23***	0.47	4.50***
Thefts	-2.59***	-0.52	9.31***
Robberies	-0.54	0.93	12.27***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A3.28: Gender effect: z-score results.

	All - Men	All - Women	Men - Women
Homicides	0.16	0.78	0.59
Assaults	-0.32	1.97**	2.91***
Sex crimes	0.22	2.23**	1.32*
Thefts	-0.16	0.25	2.85***
Robberies	0.02	1.65**	1.45*

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A3.29: Alcohol and Non alcohol estimates.

	Alcohol	No Alcohol	All	Alcohol + No Alcohol
Homicides	0.000034	-0.000068	0.00001	-0.000034
Assaults	0.004***	0.0235***	0.0277	0.0275
Sex crimes	0.0005**	0.00232***	0.003	0.00282
Thefts	0.0081***	0.1949***	0.191	0.203
Robberies	0.001**	0.0016	0.0035	0.0026

Note: Results multiplied by the clearance rate based on Table 3.4.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure A3.1: Mean monthly temperature among years.

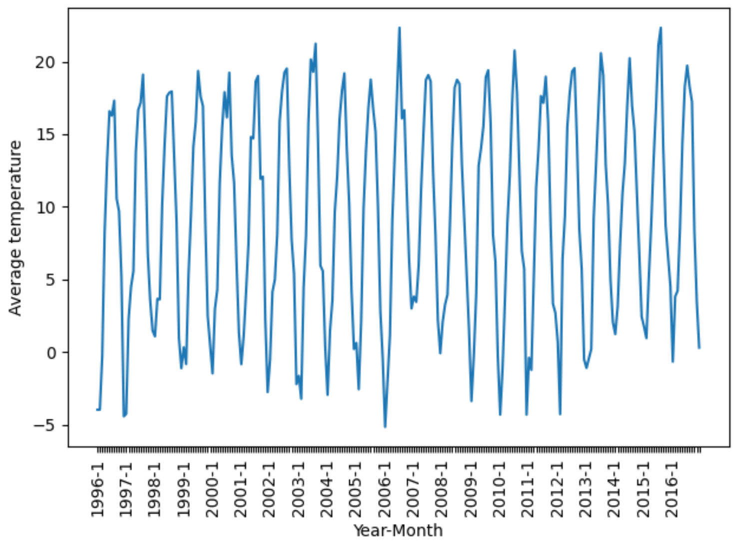


Table A3.30: Men and Women estimates.

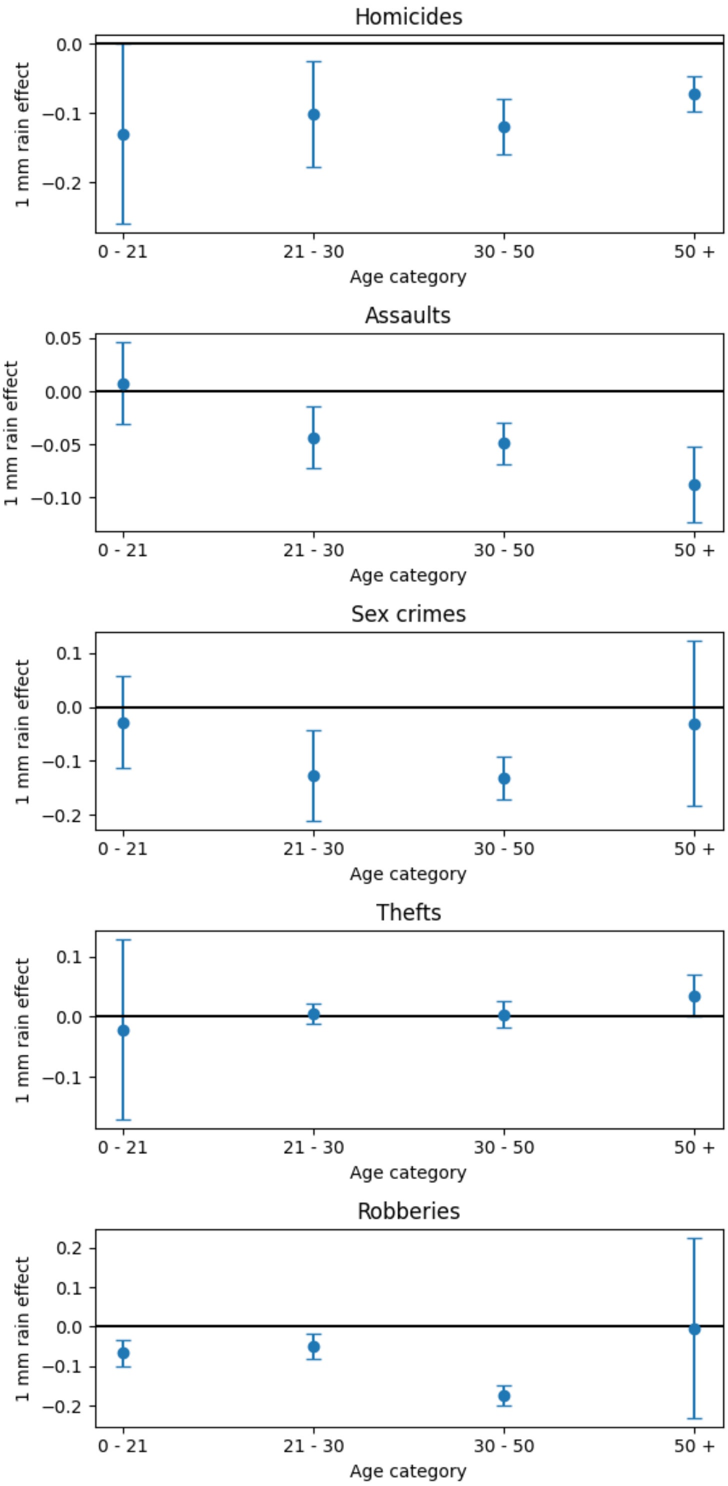
	Men	**Women**	**All**	**Men + Women**
Homicides	-0.000011	-0.000023	0.00001	-0.000033
Assaults	0.0269***	0.0018***	0.0277***	0.0287
Sex crimes	0.0028***	0.00004	0.003***	0.00284
Thefts	0.1983***	0.0125***	0.191***	0.2108
Robberies	0.0025	0.00005	0.0035**	0.00255

Note: Results multiplied by the clearance rate based on Table 3.4.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A3.31: R^2 from corresponding regressions.

	All	**Alcohol**	**Non Alcohol**	**Men**	**Women**
Homicides	0.001	0.001	0.001	0.001	0.001
Assaults	0.126	0.04	0.084	0.101	0.014
Sex crimes	0.018	0.022	0.013	0.014	0.001
Thefts	0.410	0.022	0.208	0.210	0.036
Robberies	0.058	0.004	0.025	0.025	0.004

Figure A3.2: Age decomposition of precipitation effect on crime categories



Robustness checks

Table A3.32: Results of Moran I test for spatial autocorrelation

Crime type	Moran I statistic	p-value
Homicides	-0.175	0.986
Assaults	-0.126	0.830
Thefts	-0.085	0.837
Robberies	-0.240	0.999
Sexual crimes	-0.085	0.837

Table A3.33: Effect of Extreme Temperature on Crime Rates

	Homicides	Assaults	Sex crimes	Thefts	Robberies
Extreme temperature	0.0002	0.145***	0.033***	0.443**	-0.013
	(0.002)	(0.030)	(0.008)	(0.154)	(0.016)
Intercept	0.012	3.048***	0.144***	75.627***	1.778***
	(0.008)	(0.152)	(0.040)	(0.788)	(0.081)
Observations	571,500	571,500	571,500	571,500	571,500
R^2	0.001	0.126	0.018	0.410	0.059

Note: $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$. (White 1980) robust SEs in parentheses clustered on the district level. The dependent variable is the number of crimes per 1,000,000 population. *Extreme temperature* equals 1 if the daily temperature is above the 70th percentile, and 0 otherwise.

Table A3.34: Effect of Extreme Temperature Categories on Crime Rates

	Homicides	Assaults	Sex crimes	Thefts	Robberies
80–90th percentile	0.002	0.078**	0.028**	0.093	0.016
	(0.002)	(0.033)	(0.009)	(0.174)	(0.018)
90–98th percentile	0.002	0.161***	0.022*	0.206	0.006
	(0.002)	(0.039)	(0.010)	(0.200)	(0.021)
98–100th percentile	-0.000	0.082	-0.035*	-0.326	-0.026
	(0.004)	(0.068)	(0.018)	(0.354)	(0.036)
Intercept	0.012	3.049***	0.144***	75.639***	1.778***
	(0.008)	(0.152)	(0.040)	(0.788)	(0.081)
Observations	571,500	571,500	571,500	571,500	571,500
R^2	0.001	0.126	0.018	0.410	0.059

Note: $^{*}p < 0.01$; $^{**}p < 0.05$; $^{***}p < 0.01$. (White 1980) robust SEs in parentheses clustered on the district level. The dependent variable is the number of crimes per 1,000,000 population. The omitted (baseline) category is 0–80th percentile of temperature.

Table A3.35: Effects of Temperature and Weekend on Crime Rates

	Homicides	Assaults	Sex crimes	Thefts	Robberies
1. Cold Day (Bottom 10%)					
Intercept	0.0086	3.1737***	0.1511***	77.3691***	1.8267***
	(0.0085)	(0.1542)	(0.0402)	(0.7990)	(0.0823)
Cold dummy	0.0048**	-0.1682***	-0.0088	-2.3872***	-0.0678***
	(0.0019)	(0.0353)	(0.0092)	(0.1831)	(0.0189)
2. Three Hot Days in a Row					
Intercept	0.0121	3.0499***	0.1447***	75.6194***	1.7783***
	(0.0083)	(0.1521)	(0.0397)	(0.7881)	(0.0812)
Three hot in a row	-0.0070	0.8206	-0.0280	8.5202**	-0.2634
	(0.0347)	(0.6333)	(0.1652)	(3.2821)	(0.3381)
3. Max Temperature in the Week					
Intercept	0.0121	3.0519***	0.1447***	75.6408***	1.7776***
	(0.0083)	(0.1521)	(0.0397)	(0.7881)	(0.0812)
Max temp in week	-0.0196	-0.3307	-0.0840	-0.4803	-0.0835
	(0.0121)	(0.2211)	(0.0577)	(1.1459)	(0.1180)
4. Weekend Effect					
Intercept	0.0122	3.1611***	0.1607***	76.2280***	1.7957***
	(0.0084)	(0.1523)	(0.0397)	(0.7894)	(0.0813)
Avg temp	-0.000002	0.0255***	0.0022***	0.1967***	0.0026*
	(0.00013)	(0.00241)	(0.00063)	(0.01251)	(0.00129)
Weekend	0.00026	0.0482	-0.0196*	-4.5672***	-0.1833***
	(0.00206)	(0.03749)	(0.00978)	(0.19426)	(0.02002)
Avg temp × Weekend	0.000041	0.0075	0.0027**	-0.0210	0.0029**
	(0.00012)	(0.01226)	(0.00059)	(0.01170)	(0.00121)
5. Public Holiday Effect					
Intercept	0.0122	3.1387***	0.1529***	76.2342***	1.7873***
	(0.00835)	(0.15224)	(0.03971)	(0.78873)	(0.08129)
Avg temp	0.000022	0.0266***	0.0028***	0.1724***	0.0028*
	(0.00013)	(0.00233)	(0.00061)	(0.01208)	(0.00125)
Public holiday	0.0056	-0.2306**	-0.0157	-6.5637***	-0.2385***
	(0.00386)	(0.07037)	(0.01835)	(0.36454)	(0.03757)
Avg temp × Public holiday	-0.000236	0.0346***	0.0086***	0.4419***	0.0174***
	(0.00033)	(0.00606)	(0.00158)	(0.03137)	(0.00323)
N	571,500	571,500	571,500	571,500	571,500
R^2	0.080	0.029	0.034	0.034	0.024

Notes: Dependent variable is crime rate per 1,000,000 inhabitants. Cold day = bottom 10% of average daily temperature. Three hot days in a row = indicator equals 1 if at least three consecutive days in a month are among the hottest three. Max temperature in week = indicator equals 1 for the single hottest day within a given ISO week. Weekend = 1 for Saturday and Sunday. Public holiday = Czech public holidays including Easter. All models include district, year-month, and weekday fixed effects. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.36: Effects of high temperature on crime rates

	Homicides	Assaults	Sex crimes	Thefts	Robbery
Panel A: Temperature > 25° C					
Hot day dummy	-0.00182	-0.05236	-0.04103$^{\cdot}$	-0.53798	-0.02948
	(0.00496)	(0.09045)	(0.02359)	(0.46874)	(0.04829)
Intercept	0.01212	3.05212***	0.14478***	75.64251***	1.77769***
	(0.00834)	(0.15207)	(0.03966)	(0.78809)	(0.08119)
Panel B: Temperature > 30° C					
Hot day dummy	-0.00231	-0.74205	-0.08194	-13.58116*	-0.23424
	(0.06416)	(1.17020)	(0.30522)	(6.06454)	(0.62476)
Intercept	0.01212	3.05205***	0.14467***	75.64249***	1.77763***
	(0.00834)	(0.15207)	(0.03966)	(0.78809)	(0.08119)
N	571,500	571,500	571,500	571,500	571,500
R^2	0.080	0.029	0.034	0.034	0.024

Notes: Dependent variable is crime rate per 1,000,000 inhabitants. All models include district, year-month, and weekday fixed effects. Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.05$, $^{\cdot}p < 0.10$.

Table A3.37: Case-level regressions of clearance rates by crime category

	Homicide	Assaults	Sex	Thefts	Burglary
Intercept	0.9322**	0.8706***	0.5810***	0.1160***	0.3807***
	(0.3318)	(0.0482)	(0.1511)	(0.0082)	(0.0921)
Temperature	-0.0004	-0.0008***	0.0008	-0.0015***	0.0007.
	(0.0012)	(0.0002)	(0.0006)	(0.0001)	(0.0004)
Rain	0.0009	0.0004	0.0004	0.0003**	-0.0005
	(0.0014)	(0.0003)	(0.0008)	(0.0001)	(0.0006)
N	2,014	115,463	16,966	302,565	39,365
R^2	0.080	0.029	0.034	0.034	0.024

Significance: *** p<0.01, ** p<0.05, * p<0.1

Chapter 4

Temperature and Productivity in Soccer

Abstract

This paper examines the impact of temperature on soccer team productivity using match-level data from ten countries across three continents. The results show that temperature affects multiple performance metrics, often in non-linear ways. Specifically, attacking efficiency is enhanced in warmer conditions, leading to increased goal productivity and improved shot conversion rates. Conversely, defensive performance appears to weaken in warmer conditions, with a decrease in defensive pressure and passing accuracy. Player aggression follows an inverted U-shaped pattern in relation to temperature. The effects of temperature vary across different leagues and climate regions. The relationship between temperature and outcome measures tends to be stronger in lower leagues, while the Champions League is the least influenced overall. Teams from colder regions experience a larger decline in passing volume when playing in high temperatures, with the effect being particularly pronounced in Brazil.

4.1 Introduction

Concerns about global warming are making it more urgent to understand how environmental factors, especially temperature, affect human activities and economic outcomes. While climate models predict significant temperature shifts, how these changes translate into real impacts on sectors like labor productivity is still a key area of economic research ((Dell *et al.* 2014; LoPalo 2023)). Grasping these relationships is vital for policymakers to create effective adaptation and mitigation strategies as the climate changes.

Investigating the effects of temperature on human productivity is challenging, largely due to a shortage of relevant data ((LoPalo 2023)). Majority of existing studies often on data from specific industries, like manufacturing or agriculture, which may not fully capture the complexity of modern, team-based work (e.g. (Zhang *et al.* 2018; Chen & Yang 2019; Adhvaryu *et al.* 2020)). However, sports settings, particularly professional team sports like soccer, offer an ideal environment for empirical work. Professional soccer represents a particularly compelling and relevant setting to study the effects of weather on human productivity because it combines well-measured, high-stakes team output with complex coordination under environmental stressors. Recent empirical evidence shows that ambient temperature systematically influences both physical and technical performance metrics in elite soccer, such as running distances, sprint efforts, and team engagement, making it a valuable analog for productivity in other collaborative, high-performance contexts (Illmer & Daumann 2022; Link & Weber 2017; Wei *et al.* 2023). These settings provide the features of natural experiments with clean observability, precise measurement, and high stakes, offering the best of both laboratory and field features (Palacios-Huerta 2023). This paper leverages these advantages by investigating the impact of temperature on human productivity, utilizing a comprehensive dataset of professional soccer matches. The use of soccer data offers a uniquely compelling case for several reasons. First, it provides a strong empirical analog for studying productivity in team-based, high-stakes environments. Professional soccer players are highly compensated professionals whose work requires a complex mix of physical exertion, strategic thinking, and precise collaboration under pressure. In this way, their work has key parallels to a variety of modern professions, from surgical teams to high-stakes finance, where a complex, observable output is the result of team-level effort (e.g. (O'Logbon 2020) or (Catchpole *et al.* 2008)). Second, the soccer data setting allows for the clear and objective measurement of productivity. While professional soccer can be view as a profit-driven show business, the on-field performance of the teams and players is the fundamental driver of that commercial success. Ticket sales, broadcast rights, and sponsorships all depend on a team's ability to win and perform at a high level. I have analyzed the direct factors influencing football performance, including attacking efficiency (goals scored and shot conversion), team effort (number of shots), and player cooperation (pass accuracy). These metrics form the core of my definition of productivity. I also investigate how temperature affects player aggression, as measured by fouls and cards. Thanks to the rich dataset, I can also compare the impact of temperature on players from different leagues and determine whether local players adapt better to warmer temperatures.

Productivity in soccer should be understood as a reduced-form, audience-oriented concept rather than a measure of individual output. Observable outcomes (e.g., a goal, a successful pass, a blocked shot) arise from interactions between opposing teams and from joint performance of multiple players. As a result, any attribution of productivity to a specific group remains inherently ambiguous and reflects interaction effects rather than isolated contributions[1].

This is the first study to analyze the effects of temperature on soccer productivity using a large-scale dataset from top-tier leagues across three continents. Using panel data models with team-season and region-season fixed effects, I isolate the impact of temperature on performance. The findings show that warmer conditions can enhance productivity, as teams score more goals and convert set-piece opportunities more effectively. At the same time, defensive performance weakens, and player aggression follows an inverted U-shaped pattern, rising with temperature before falling at extreme heat levels.

The sensitivity to temperature fluctuations is observed to vary across different leagues and in relation to climatic origins. For instance, teams originating from colder regions appear to experience greater difficulty with passing accuracy in high-temperature environments, particularly in the case of Brazilian leagues. Additionally, the magnitude of the temperature effect differs across league levels, with a more pronounced increase in fouls observed in second divisions and a less significant decline in passing accuracy compared to top-tier leagues. Notably, the Champions League appears to be the least susceptible to variations in temperature.

The rest of the paper is structured as follows. Section 4.2 provides an overview of the related literature, Section 4.3 provides a summary of the data. Section 4.4 details the identification strategy of the models used in the analysis, and Section 4.5 discusses the key findings. Finally, Section 4.6 concludes the paper.

[1]Formally, the model is described in Appendix Section 4.6.

4.2 Related Literature

Investigating weather effects on worker-level is challenging especially because the data is usually in short supply. Therefor, some of the existing studies are made on employee data from individual firms, while other use firm-level datasets, (LoPalo 2023). The literature on human physiology suggests that people's productivity drops quickly when they are forced to work in uncomfortable temperatures (i.e. (Anderson 1989) or (Cramer & Jay 2016)). (Deschênes & Greenstone 2007) estimates the impact of climate change on US agricultural profits, revealing modest overall effects with significant regional variation. According to existing studies, higher temperatures generally exhibit a negative correlation with productivity and economic output, particularly in warmer climates, while cooler regions experience marginal gains. Deviations from optimal temperature ranges, especially towards higher values, induce performance decline.

A related body of research examines the relationship between temperature and crime. (Baysan *et al.* 2019) report that higher temperatures are associated with increases in both interpersonal and organized violence. (Heilmann *et al.* 2021) find that crime rates rise on hotter days, particularly for crimes of passion, and that characteristics of the built environment (e.g., urban greenery) reduce this relationship. (Horrocks & Menclova 2011) show that temperature significantly increases violent and property crimes, while precipitation reduces violent crime. (Mišák 2022) find that temperature significantly increases assaults, thefts, robberies, and sexual crimes, whereas precipitation decreases assaults and sexual crimes.

Higher temperatures also affect decision-making. (Heyes & Saberian 2019) document that elevated temperatures systematically reduce favorable rulings by U.S. immigration judges, suggesting that heat impairs judicial decision quality.

(Fischer & Haucap 2022) analyze professional soccer matches and find that external shocks, such as the absence of spectators during the COVID-19 pandemic, influence refereeing and betting market behavior, thereby affecting the home advantage. (Gavresi *et al.* 2024) study how marginal changes in temperature shape individual financial decision-making depending on personality traits, finding that higher temperatures increase the probability that optimists invest in bonds and decrease the probability that they invest in stocks, while no significant effects are observed for pessimists. (Stadelmann *et al.* 2023) show that higher temperatures affect media decision-making by increasing partisan bias in news coverage. Together, these studies indicate that higher temperatures tend to lead to less favorable or less professional decisions.

(Joly & Dik 2021) examined the impact of cold weather on the National Football League (NFL) and found a statistically significant home-field advantage for teams playing in cold weather climates during the winter months. This advantage suggests that extreme weather conditions can indeed influence game outcomes, particularly in sports played outdoors. (Burke *et al.* 2023) investigated the effects of hot temperatures on professional tennis performance. This research revealed that high temperatures lead to increased errors and retirements, as well as reduced win probability in subsequent matches. The study found that top players were less affected by heat and that there was no adaptation to heat shown by the athletes.

(Koch & Panorska 2013) analyzed Major League Baseball (MLB) games from 2000-11, finding that warm temperatures significantly increase offensive production, including runs scored, batting average, and home runs, while decreasing walks. The American League showed a stronger temperature impact than the National League. (Fesselmeyer 2021) examined the effect of temperature on MLB umpire accuracy, revealing that high temperatures significantly decrease the accuracy of ball and strike calls.

(Picchio & Van Ours 2024) examine how high temperatures affect the performance of professional tennis players during outdoor singles matches at major tournaments. The results show that player performance declines significantly with rising temperatures, although the effect is less pronounced when more is at stake or when players have had time to adapt to the heat. These findings are consistent across genders and remain robust when accounting for wind speed and air pollution.

Prior research on environmental effects in soccer has primarily focused on data from the Chinese Super League (CSL), the top professional league in Mainland China[2]. (Yuan *et al.* 2024) found that elevated temperatures and precipitation during matches lead to a significant decrease in total running distances, the number of passes, and the number of fouls, with these effects being more pronounced for away teams. (Wei *et al.* 2023) posits an inverted-U shaped relationship between temperature and players' physical performance. Conversely, scholars such as (Zhou *et al.* 2019) and (Zhang *et al.* 2024) found

[2]Note that these existing studies are based on relatively small data samples compared to this paper, with a maximum of four seasons analyzed.

only a negligible impact of relative air humidity and air quality index on the performance of soccer players in the CSL league.

4.3 Data

The analysis focuses on data from the Champions League and the following countries: UK, Germany, Spain, Italy, Portugal, France, Netherlands, Brazil, Argentina, and USA. The data are structured at the match level, where each individual match is represented by two distinct records, corresponding to the home and away teams involved. This structure allows for panel data analysis, tracking the same teams across different match weeks and seasons. This article uses data from two sources: soccer data from LIVESPORT[3] and weather data from the OpenWeather API, matched using the home team geo-coordinates at the exact time of kick-off.[4] Precipitation is coded as a dummy equal to 1 if rainfall > 0 mm is recorded during the same day[5], and temperature is measured in °C at kick-off. Data covers the period from 2006 to 2024 and not all variables are available for all states and leagues (see Table A4.29 and Table A4.30 for a detailed description of which data is available for which league). For the purposes of measuring a team's productivity in a game, I divided the variables into three main categories: Attacks, Defense & Possession and Aggression. An overview, including subcategories, is provided in Table 4.1.

Figure 4.1 shows histograms of temperatures across countries and leagues. The coldest weather is in the UK and the Champions League, while the warmest weather is in Brazil, Argentina and the USA. Table A4.28 shows the variation in temperatures within each country. While in the Netherlands, Germany or the UK the average differences between home teams are minimal, in Spain, Brazil and the USA the difference between the coldest and warmest home football team is more than 10'C. The variation in temperature therefore occurs across time, as the league season progresses towards warmer or colder weather, and across locations as teams travel to colder or warmer places. Figure A4.1 illustrates temperature deviations per week within each country and indicates

[3]http://www.livesport.cz

[4]https://openweathermap.org/api

[5]It is not possible to use information on retractable roofs, since their presence does not imply they were closed during rain. Roof closure is decided by the referee and UEFA match delegate, and in some cases (e.g., strong winds) closure is not allowed (UEFA Regulations, Art. 34).

the timing of winter and summer breaks across the leagues. Table A4.31, Table A4.33, and Table A4.32 present summary statistics for all productivity variables across countries. Moreover, the appendix contains country- and league-level weather statistics, comprehensive data availability tables, regression outputs including robustness checks with linear temperature trends and temperature–precipitation interactions, and graphs on the estimated temperature effects across a wide range of soccer productivity metrics.

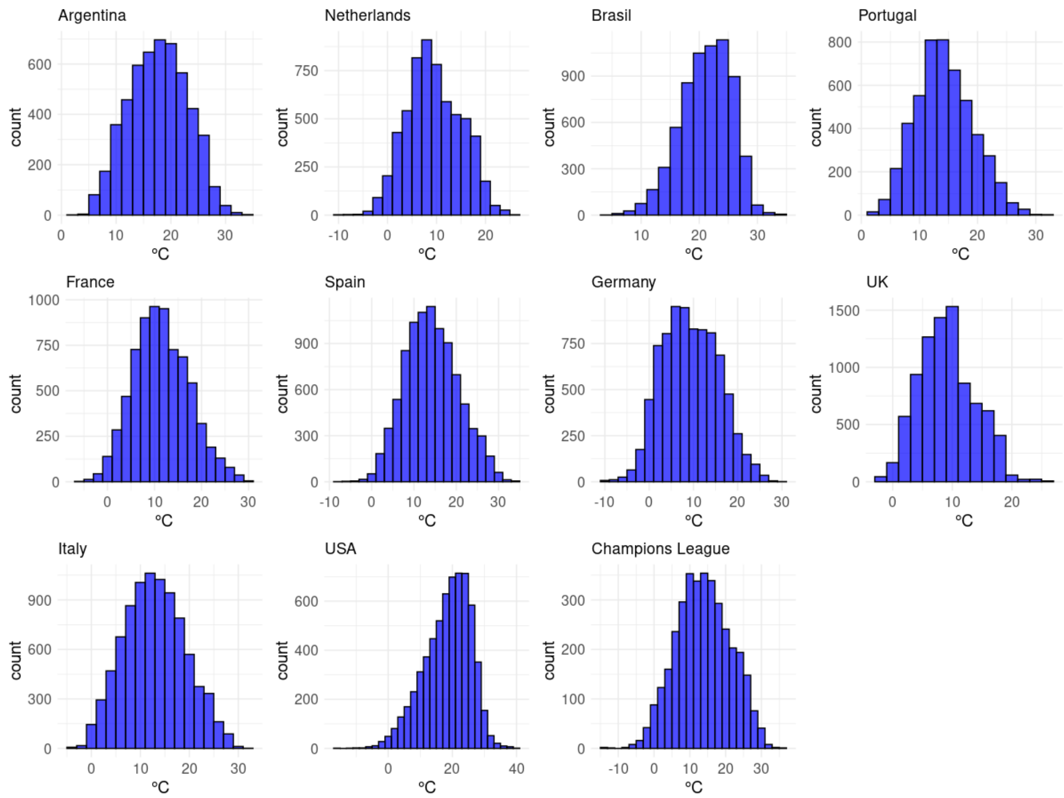
Table 4.1: Metrics for Measuring Football Team Productivity

Attacks	
Total Score	Score
Score per Shot	Score / Total shots
Score per Shot on Target	Score / Shots on target
Total Shots	Total shots
Total Shots on Target	Total shots on target
Shooting Accuracy	Shots on target / Total shots
Corners	Total number of corners
Corner Conversion Rate	Score / Corners
Free Kicks	Total number of free kicks
Free Kick Conversion Rate	Score / Free kicks
Defense & Possession	
Shot Blocking Rate	Blocked shots / Total shots
Passes	Total number of passes
Passing Accuracy	Successful passes / Passes
Aggression	
Fouls	Total number of fouls
Yellow cards	Total number of yellow cards
Red cards	Total number of red cards

4.4 Methodology

In this section, I develop an econometric model to examine the relationship between weather and soccer-related productivity. The identification strategy is presented in three specifications. Equations Equation 4.1, Equation 4.2, and Equation 4.4 include a comprehensive set of fixed effects to control for time-invariant unobserved heterogeneity that might be specific to a particular country, league, or team. Specifically, the identification strategies employ a within

Figure 4.1: Histogram of temperatures in leagues.



time-country approach, isolating variations in temperature across matches.[6] [7]

4.4.1 Identification strategy

The main specification examines the effect of temperature on productivity by dividing the temperature variable into six bins: $< 6°C$, $6 - 10°C$, $10 - 14°C$, $14 - 18°C$, $18 - 22°C$, and $\geq 22°C$ (Equation 4.1). This binning was chosen to ensure that the specification captures the full range of temperatures observed across all leagues and countries (recall Figure 4.1). A middle bin of $10 - 14°C$ serves as the omitted category. The choice of $10 - 14°C$ as the omitted category is based on the prior literature, which finds that $10 - 14°C$ is associated with highest performance and productivity ((Burke *et al.* 2015;

[6]As a robustness check, regressions were also run exclusively on teams participating in the Champions League.

[7]Since temperature and precipitation patterns on a particular day may be correlated across geographic areas, I cluster all standard errors at the home stadium level. The productivity variables, which are count variables (such as the number of fouls or goals per game), are modeled using Poisson regression, while the remaining variables are estimated using OLS regression.

Pavlinovic *et al.* 2024)). Moreover, a recent review by (Lai *et al.* 2023) highlights that temperature-bin approaches are particularly suitable for detecting nonlinearities in the relationship between temperature and labor productivity. Alternative approaches such as semi-parametric methods are less appropriate in this context, since the uneven distribution of observed temperatures across countries would generate large estimation uncertainty at the extremes and hinder comparability.

Identification relies on within–stadium-year variation in temperature. The empirical model includes fixed effects for the home team stadium-by-year (capturing the location where the match was played), the away team-by-year, and the referee in a given season. These fixed effects absorb differences in climate across locations, season-specific performance, as well as systematic differences in refereeing. As a result, the coefficients on the temperature bins reflect relative deviations from the reference category within a given stadium-year, rather than absolute differences across the entire sample. The omitted category (10˘14°C) thus serves as a benchmark only within each stadium-year, not in absolute terms across leagues or countries. Remaining environmental confounders such as precipitation are explicitly controlled for. [8] The empirical strategy therefore follows a quasi-experimental logic in which short-run fluctuations in weather conditions are plausibly exogenous to team performance.

The same bin structure is applied across all countries to ensure comparability of the estimated effects. Robustness checks incorporating linear temperature trends and temperature–precipitation interactions are discussed in Subsection 4.5.4. The main estimated regression has the following form:

$$Productivity_{s,d} = \sum_{i=1}^{6} \alpha^i \cdot T^i_{s,d} + \beta^P \cdot P_{s,d} + FE + \epsilon_{s,d} \qquad (4.1)$$

Where $T^i_{s,d}$ stand for the six temperature bins, P denotes precipitation dummy, FE is the set of fixed effects and $\epsilon_{s,d}$ stands for the error term. All in day d and stadium s. I incorporate fixed effects for the home team stadium-by-year (which also represents the location where the match was played), away

[8] While it is possible that other environmental variables, such as air pollution, may also affect soccer productivity, suitable data are not available for the full sample of 11 countries. Moreover, evidence from smaller-scale studies (e.g., (Picchio & Van Ours 2024)) suggests that air pollution does not bias short-run estimates of temperature effects on sporting outcomes.

team-by-year fixed effects, and the referee in a given season.

Another possible hypothesis is that teams that come from climatically different places are more sensitive to temperature. Therefore, in Equation 4.2, I test whether teams from the coldest cities react differently to high temperatures when they play in a high-temperature environment. In other words, this part examines whether players can adapt equally well regardless of where they are used to playing home games and training. This analysis is done for leagues from three states – the USA, Brazil, and Spain – because only there is sufficient within-state variability in mean temperature (see Table A4.28):

$$\begin{aligned} Productivity\_away_{s,d} = \beta^T \cdot T^E_{s,d} + \beta^{TC} \cdot T^E_{s,d} \cdot Climate_{s,d} \\ + \beta^C \cdot Climate_{s,d} + \beta^P \cdot P_{s,d} + FE + \epsilon_{s,d} \end{aligned} \tag{4.2}$$

Where $Productivity\_away_{s,d}$ denotes the productivity variable measured for the visiting team. An alternative approach refines this idea by dividing teams into three climate groups based on the mean temperature of their home locations. Specifically, teams are categorized into terciles within each country: the coldest third, the middle third, and the warmest third. This specification allows for a more granular test of climate adaptation effects by accounting for a broader range of climatic conditions teams are accustomed to.

$$\begin{aligned} Productivity_{s,d} = \beta^{away} \cdot D\_away + \beta^{away\_Climate} \cdot D\_away \cdot Climate\_group \\ + \beta^{away\_Climate\_temp} \cdot T \cdot D\_away \cdot Climate\_group + FE + \epsilon_{s,d} \end{aligned} \tag{4.3}$$

In Equation 4.3, $Climate\_group$ is a categorical variable dividing teams into terciles based on the long-term average temperature of their home location, rather than a binary classification. The term D_away is an indicator for whether the team is playing an away game. T stands for the temperature during the match. The interaction term $D\_away \cdot Climate\_group$ captures differences in away-game performance across climate terciles, while $T \cdot D\_away \cdot Climate\_group$ measures whether these differences are further moderated by high temperatures on game day. To isolate the temperature effect, I use fixed effects for home team stadium-by-year, away team stadium-by-year, and referee-season. This approach improves on Equation 4.2 by allowing for more variation in climate adaptation effects, rather than restricting the comparison to only the coldest teams versus the rest.

Finally, the paper tests the hypothesis whether the effect of temperature is different for different divisions. In other words, whether players adapt to high temperatures differently when playing in the top league in their country than when playing in lower leagues. Therefore, Equation 4.4 examines the interaction between the dummy variable Div (equals 1 based on whether the match is played in the top division, or second, third top league, or European champions league.) and the dummy variable T^{22+} which is equal to 1 if the match was played in more than 22 degrees Celsius on that day, otherwise 0 - the same temperature threshold as in the Equation 4.1:

$$Productivity_{s,d} = \beta^{T22+} \cdot T^{22+}_{s,d} + \beta^{TDiv} \cdot T^{22+}_{s,d} \cdot Div + \beta^{Div} \cdot Div + \beta^{P} \cdot P_{s,d} + FE + \epsilon_{s,d} \tag{4.4}$$

4.5 Results

In general, the results portray a complex relationship between temperature and a soccer team productivity, assessed using a variety of performance measures. Certain gameplay elements tend to vary non-linearly (inverted U-shape relationship) with temperature changes, while others exhibit a clear threshold effect when temperatures are high.

Compared to the baseline temperature range of 10–14°C, matches contested in conditions exceeding 22°C demonstrate a statistically significant enhancement in overall goal productivity, Figure 4.2. Specifically, teams achieve a greater number of goals, exhibit improved shot conversion rates (both overall and on-target), and undertake a higher volume of both total and on-target shots (Table 4.2). Furthermore, the efficiency of set-piece situations is augmented, as evidenced by elevated conversion rates from both corner kicks and direct free kicks (Table 4.2). This suggests that attacking play becomes more efficacious in elevated temperature environments.[9]

Conversely, defensive performance experiences a decline under higher temperature conditions, Figure 4.3. The number of blocked shots decreases, indicative of diminished defensive pressure (Table 4.3). Moreover, teams concede a greater number of goals from set pieces, which suggests a weakening in defensive organization during these scenarios. Game control is also negatively impacted, as evidenced by a reduction in the total number of passes and passing accuracy (Table 4.3). This decline in structured play and defensive stability implies that elevated temperatures disrupt coordinated team movements and defensive cohesion, thereby complicating the maintenance of match control.

A similar pattern emerges for the total number of corners taken, indicating that attacking teams generate more set-piece opportunities under moderate temperature conditions, yet this trend reverses in instances of extreme heat (Table 4.2).

The observed effects on passing patterns are particularly pronounced within the United Kingdom and the Netherlands, implying that teams competing in these leagues may exhibit greater sensitivity to temperature fluctuations. However, within the context of the UEFA Champions League, these temperature-related effects are either negligible or statistically insignificant.

In summation, these findings underscore that while elevated temperatures contribute to a reduction in defensive stability and passing efficiency, they simultaneously foster a more direct attacking style of play. The inverted U-shaped pattern observed in set-piece generation further accentuates the necessity of considering non-linear effects when evaluating the influence of environmental factors on team performance.

Overall, while temperature impacts team performance, the observed effects vary in magnitude. Relative to temperature range of 10–14°C within the same stadium-year context, matches played in temperatures exceeding 22°C are associated with a 2.6% increase in total scoring, a 3.4% improvement in scoring efficiency per shot on target, a 6.4% increase in corner conversion rate, and the free kick conversion rate rises by 12.5% under warmer conditions. Moreover, teams complete 2.9% fewer passes, shot-blocking effectiveness drops by 2.5%.

Beyond the on-field performance metrics, my research also reveals a relationship between temperature and match attendance. As detailed in Table 4.5 and Figure A4.10, elevated temperatures appear to positively influence specta-

[9]Keeping in mind that each observed effect reflects combined actions of multiple players, not isolated individual performance.

tor turnout. Specifically, matches played in conditions exceeding 22°C demonstrate a 2.6 percentage point increase in attendance compared to the baseline temperature range of 10–14°C. This suggests that better attacking efficiency fostered by higher temperatures, which leads to a greater number of goals and improved shot conversion rates, further contributes to increased attractiveness for spectators, alongside the inherent appeal of favorable weather conditions.

4.5.1 Aggression

An inverted U-shaped relationship is observed between temperature and metrics of aggressiveness, encompassing the number of fouls committed and the issuance of yellow cards (Table 4.4). This suggests that player aggression intensifies with rising temperatures up to a certain point, before subsequently diminishing at excessively high heat levels.

The observed effects on foul-related behavior are particularly pronounced within the United Kingdom and the Netherlands, implying that teams competing in these leagues may exhibit greater sensitivity to temperature fluctuations. However, within the context of the UEFA Champions League, these temperature-related effects are either negligible or statistically insignificant.

Finally, I test whether the team with a higher number of unsuccessful passes tends to commit more fouls in higher temperatures. Based on the results in Table 4.6, the team with a higher ratio of successful passes commits less fouls and receives fewer yellow cards; however, this effect is not particularly pronounced at higher temperatures.

Overall, while temperature impacts aggression, the observed effects vary in magnitude. Relative to temperature range of 10–14°C within the same stadium-year context, matches played in temperatures exceeding 22°C are associated with an 11.6% increase in the number of committed fouls.

Table 4.2: Regression Results - Attacks

	Dependent variable:									
	Poisson Total Score	*OLS* Score per Shot	*OLS* Score per Shot on Target	*Poisson* Total Shots	*Poisson* Total Shots on Target	*OLS* Shooting Accuracy	*Poisson* Corners	*OLS* Corner Conversion Rate	*Poisson* Free Kicks	*OLS* Free Kick Conversion Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
< 6 °C	-0.030^{***}	-0.003^{***}	-0.014^{***}	-0.004	0.009^{*}	0.005^{**}	-0.010^{**}	-0.008^{*}	0.001	-0.002
	(0.009)	(0.001)	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.004)	(0.003)	(0.002)
6–10 °C	-0.013	-0.001	-0.005^{**}	-0.003	0.004	0.002	-0.005	-0.003	0.005^{*}	-0.001
	(0.008)	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)	(0.003)	(0.001)
14–18 °C	0.001	-0.001	0.001	0.005^{**}	-0.003	-0.004^{***}	-0.004	-0.0001	-0.003	-0.001
	(0.008)	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)	(0.003)	(0.001)
18–22 °C	0.029^{***}	0.001	0.005^{*}	0.014^{***}	0.002	-0.005^{***}	-0.001	0.006	-0.018^{***}	0.003^{**}
	(0.009)	(0.001)	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.004)	(0.003)	(0.002)
> 22 °C	0.066^{***}	0.003^{**}	0.010^{***}	0.024^{***}	0.026^{***}	-0.001	-0.009^{*}	0.018^{***}	-0.039^{***}	0.010^{***}
	(0.011)	(0.001)	(0.003)	(0.003)	(0.006)	(0.002)	(0.005)	(0.005)	(0.004)	(0.002)
Rain	0.014^{***}	0.001	0.003^{**}	0.009^{***}	0.006^{**}	-0.001	0.013^{***}	-0.001	-0.004^{**}	0.002^{***}
	(0.005)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Constant	0.728^{***}	0.121^{***}	0.244^{***}	3.005^{***}	2.180^{***}	0.476^{***}	2.199^{***}	0.290^{***}	1.010^{***}	0.092
	(0.080)	(0.009)	(0.022)	(0.025)	(0.042)	(0.014)	(0.040)	(0.033)	(0.200)	(0.087)
Observations	75,044	74,915	74,874	74,915	74,912	74,911	74,912	74,909	52,352	52,315
(Pseudo) R^2	0.10	0.09	0.09	0.14	0.11	0.12	0.11	0.09	0.10	0.12
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Omitted category mean (10–14 °C)	2.59	0.11	0.29	24.02	9.03	0.38	9.88	0.28	31.99	0.08

Note: < 6 °C, 6–10 °C, 14–18 °C, 18–22 °C and > 22 °C stand for temperature bins. 10–14 °C is the omitted category. Rain is a dummy variable for precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table 4.3: Regression Results - Defense & Possession

	Dependent variable:		
	OLS	*OLS*	*OLS*
	Shot blocking rate	Passes	Passing accuracy
	(4)	(5)	(6)
< 6 °C	0.002	0.226***	0.743***
	(0.002)	(0.001)	(0.086)
6−10 °C	0.002*	0.139***	0.384***
	(0.001)	(0.001)	(0.069)
14−18 °C	0.001	−0.081***	−0.214***
	(0.001)	(0.001)	(0.067)
18−22 °C	−0.001	−0.120***	−0.340***
	(0.002)	(0.001)	(0.079)
> 22 °C	−0.006***	−0.256***	−0.720***
	(0.002)	(0.001)	(0.092)
Rain	0.001	0.017***	0.045
	(0.001)	(0.0004)	(0.042)
Constant	0.164***	6.622***	1.106
	(0.017)	(0.006)	(0.724)
Observations	52,532	37,870	23,380
(Pseudo) R^2	0.09	0.09	0.11
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓
Omitted category mean (10–14 °C)	0.24	882.93	0.75

Note: < 6 °C, 6−10 °C, 14−18 °C, 18−22 °C and > 22 °C stand for temperature bins. 10−14 °C is the omitted category. Rain is a dummy variable for precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table 4.4: Regression Results - Aggression

	Dependent variable:		
	Poisson	*Poisson*	*Poisson*
	Fouls	Yellow cards	Red cards
	(1)	(2)	(3)
$< 6\,°C$	-0.006^{*}	-0.039^{***}	-0.018
	(0.003)	(0.008)	(0.034)
$6-10\,°C$	0.002	-0.010^{*}	-0.009
	(0.003)	(0.006)	(0.028)
$14-18\,°C$	-0.007^{***}	0.005	0.017
	(0.003)	(0.006)	(0.026)
$18-22\,°C$	-0.015^{***}	0.010	0.014
	(0.003)	(0.007)	(0.030)
$> 22\,°C$	-0.032^{***}	-0.020^{**}	0.008
	(0.003)	(0.008)	(0.035)
Rain	-0.007^{***}	0.010^{**}	-0.0001
	(0.002)	(0.004)	(0.017)
Constant	3.325^{***}	1.683^{***}	0.341
	(0.024)	(0.056)	(0.225)
Observations	68,390	72,473	14,807
(Pseudo) R^2	0.12	0.10	0.10
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓
Omitted category mean (10–14 °C)	27.66	4.60	1.07

Note: $< 6\,°C$, $6-10\,°C$, $14-18\,°C$, $18-22\,°C$ and $> 22\,°C$ stand for temperature bins. $10-14\,°C$ is the omitted category. Rain is a dummy variable for precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table 4.5: Regression Results - Attendance

	Dependent variable:
	Attendance (Percentage of stadium occupancy)
$< 6\,°C$	-3.234^{***}
	(0.386)
6−10 °C	-1.502^{***}
	(0.320)
14−18 °C	1.224^{***}
	(0.323)
18−22 °C	2.001^{***}
	(0.406)
$> 22\,°C$	2.654^{***}
	(0.492)
Rain	-0.999^{***}
	(0.197)
Constant	27.312^{***}
	(6.184)
Observations	53,142
R^2	0.56
Home team stadium-by-year FE	✓
Away team-by-year FE	✓
Omitted category mean (10−14 °C)	64.83

Note: $< 6\,°C$, 6−10 °C, 14−18 °C, 18−22 °C and $> 22\,°C$ stand for temperature bins. 10−14 °C is the omitted category. Rain is a dummy variable for precipitation. *p<0.1; **p<0.05; ***p<0.01.

Figure 4.2: Temperature Effects on Attacks

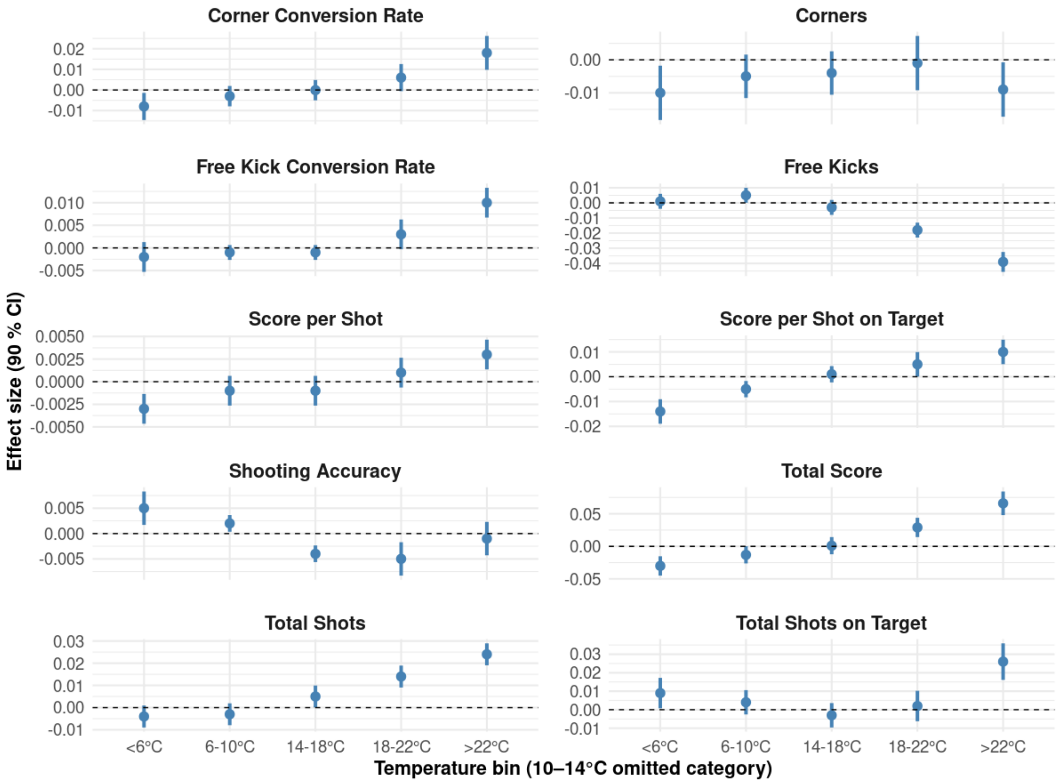
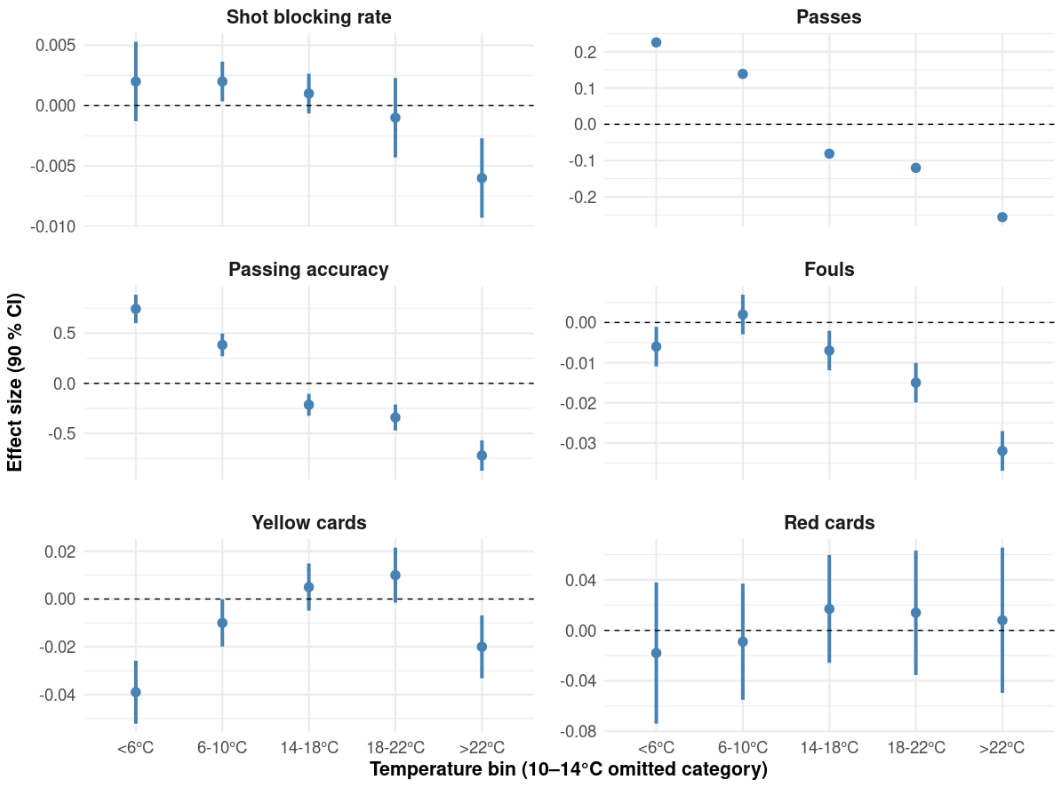


Figure 4.3: Temperature Effects on Defense, Possession and Aggression



4.5.2 Climatic Origin and Hot Weather Effects

In this paragraph I comment on whether the results in the previous main section are stronger if the club comes from a climatically cooler location and plays a match on a hot day. My analysis finds that the only performance metric significantly affected by a team's climatic origin is the total number of passes (Table 4.6 and Table 4.7). Teams from colder cities experience a stronger decline in passing volume when playing in high temperatures compared to teams from warmer locations. This effect is observed across the USA, Brazil, and Spain, with the strongest impact in Brazil. The heightened sensitivity in Brazil may be attributed to it being the warmest country in the dataset (see Table A4.28), suggesting that teams from colder regions struggle more when exposed to extreme heat in already warm climates.

Table 4.6: Impact of Climatic Origin and Heat on Passes and Passing Accuracy

	Dependent variable:					
	OLS			*OLS*		
	Passes			Passing accuracy		
	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)
Climate	-0.125^{***}	-0.313^{***}	-0.059^{***}	0.138	-1.125	0.042^{**}
	(0.004)	(0.015)	(0.006)	(0.504)	(2.947)	(0.017)
T^E	-0.023^{***}	-0.067^{***}	-0.005^{*}	-0.071	-0.974^{*}	-0.005
	(0.002)	(0.002)	(0.003)	(0.174)	(0.555)	(0.008)
Climate $\cdot T^E$	-0.070^{***}	-0.596^{***}	-0.040^{***}	-1.381	2.988	-0.011
	(0.010)	(0.016)	(0.007)	(1.729)	(4.108)	(0.021)
Constant	6.376^{***}	6.922^{***}	6.814^{***}	4.671^{*}	1.262	1.256^{***}
	(0.021)	(0.018)	(0.034)	(2.567)	(5.516)	(0.073)
Observations	4,993	3,937	3,243	2,651	2,767	1,744
(Pseudo) R^2	0.10	0.09	0.11	0.10	0.10	0.09
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓

Notes: Climate is defined as a binary variable that takes the value of 1 if the team originates from the 20% coldest cities. T^E equals 1 if the observed temperature falls within the 90th percentile of the temperature distribution. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4.7: Impact of Climatic Origin Group and Heat on Passes and Passing Accuracy

	Dependent variable:					
		OLS			*OLS*	
		Passes			Passing accuracy	
	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)
T	-0.004^{***}	-0.122^{***}	-0.001^{***}	-0.019	0.411^{***}	-0.001^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.016)	(0.077)	(0.0005)
$Climate\_2 \cdot T$	-0.008^{***}	-0.001	-0.001^{***}	-0.002	-0.097	0.0004
	(0.0002)	(0.0003)	(0.0003)	(0.024)	(0.116)	(0.001)
$Climate\_3 \cdot T$	-0.023^{***}	-0.061^{***}	0.0001	-0.031	-0.190	-0.001
	(0.0002)	(0.0005)	(0.0003)	(0.025)	(0.185)	(0.001)
Constant	7.273^{***}	4.653^{***}	6.614^{***}	2.372^{***}	-5.067	1.400^{***}
	(0.005)	(0.017)	(0.006)	(0.720)	(5.154)	(0.013)
Observations	4,993	3,937	3,243	2,651	2,767	1,744
(Pseudo) R^2	0.08	0.09	0.10	0.10	0.08	0.08
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓

Notes: T represents temperature as a continuous variable. *Climate_2* and *Climate_3* are dummy variables equal to 1 if the team falls into the middle or warmest temperature tercile within a country, respectively, and 0 otherwise. *p<0.1; **p<0.05; ***p<0.01.

4.5.3 Temperature Effects on Productivity Across League Levels

The impact of high temperatures varies across league divisions. The effect on the number of fouls is stronger in the second-highest division compared to the top league in a given country, suggesting that lower-tier teams exhibit more aggressive behavior under heat. Similarly, the number of corners is more affected in the Champions League than in the top domestic leagues, indicating that set-piece generation is more sensitive to temperature in elite international competition, Table 4.8.

Passing metrics also show differential effects. The impact of high temperatures on both the total number of passes and passing accuracy is lower in the second-highest division than in the top league, suggesting that top-tier teams experience a greater decline in structured play under heat. However, the effect on the number of passes is stronger in the Champions League than in domestic top leagues, implying that temperature influences game control more in international matches, Table 4.9 and Table 4.10.

Shooting-related metrics follow a similar pattern, with the effect on shots on target and shooting accuracy being weaker in the second-highest division compared to the top league.

Table 4.8: Temperature Effects by League Level - Attacks

	Dependent variable:						
	Poisson	*Poisson*	*OLS*	*Poisson*	*OLS*	*Poisson*	*OLS*
	Total Shots	Total Shots on Target	Shooting accuracy	Corners	Corner conversion rate	Free kicks	Free kick conversion rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T^{22+}	0.017***	0.034***	0.005**	−0.002	0.016***	−0.030***	0.008***
	(0.003)	(0.006)	(0.002)	(0.005)	(0.005)	(0.004)	(0.002)
E1	−0.047***	0.008	0.023***	0.004	−0.002	0.042***	−0.006***
	(0.004)	(0.006)	(0.002)	(0.006)	(0.005)	(0.004)	(0.002)
E2	−0.216***	−0.043**	0.077***	0.048***	−0.023*	0.083***	−0.020***
	(0.011)	(0.017)	(0.006)	(0.016)	(0.014)	(0.012)	(0.005)
Champ	0.285	0.060	−0.065	0.680	−0.512	0.371	0.022
	(0.311)	(0.534)	(0.177)	(0.468)	(0.412)	(0.268)	(0.129)
Rain	0.010***	0.005**	−0.002*	0.013***	−0.001	0.003	0.002***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
$T^{22+}\cdot$ E1	0.002	−0.031***	−0.012***	−0.014*	−0.006	−0.005	0.003
	(0.006)	(0.009)	(0.003)	(0.009)	(0.007)	(0.006)	(0.003)
$T^{22+}\cdot$ E2	−0.041	−0.054	−0.002	−0.074*	0.019	−0.009	−0.002
	(0.031)	(0.048)	(0.016)	(0.045)	(0.037)	(0.027)	(0.012)
$T^{22+}\cdot$ Champ	0.001	0.025	0.010	−0.008	0.033	0.052***	−0.010
	(0.017)	(0.027)	(0.010)	(0.027)	(0.023)	(0.018)	(0.008)
Observations	74,915	74,912	74,911	74,912	74,909	52,352	52,315
(Pseudo) R^2	0.14	0.11	0.12	0.11	0.09	0.10	0.12
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓

Notes: T^{22+} equals 1 if the observed temperature is higher than 22°. Champ, E1 and E2 stand for the Champions League, second and third highest leagues in the country. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4.9: Temperature Effects by League Level - Defense & Possession

	Dependent variable:		
	OLS	*OLS*	*OLS*
	Passes	Passing accuracy	Shot blocking rate
	(4)	(5)	(6)
T^{22+}	0.234***	0.690***	−0.004**
	(0.001)	(0.091)	(0.002)
E1	−0.021***	−0.261**	−0.002
	(0.001)	(0.117)	(0.002)
E2	−0.038***	−0.191	−0.019***
	(0.003)	(0.443)	(0.006)
Champ	−0.168***	−0.301	0.123
	(0.030)	(2.590)	(0.143)
Rain	0.030***	0.074*	0.001
	(0.0004)	(0.042)	(0.001)
$T^{22+}\cdot$ E1	−0.145***	−0.512***	−0.003
	(0.001)	(0.140)	(0.003)
$T^{22+}\cdot$ E2	−0.180***	−0.486	0.004
	(0.014)	(1.067)	(0.018)
$T^{22+}\cdot$ Champ	0.052***	0.017	−0.004
	(0.004)	(0.410)	(0.008)
Observations	37,870	23,380	52,532
(Pseudo) R^2	0.09	0.08	0.10
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: T^{22+} equals 1 if the observed temperature is higher than 22°. Champ, E1 and E2 stand for the Champions League, second and third highest leagues in the country. *p<0.1; **p<0.05; ***p<0.01.

Table 4.10: Temperature Effects by League Level - Aggression

	Dependent variable:		
	Poisson	*Poisson*	*Poisson*
	Fouls	Yellow cards	Red cards
	(1)	(2)	(3)
T^{22+}	-0.028^{***}	-0.024^{***}	-0.001
	(0.003)	(0.008)	(0.035)
E1	0.040^{***}	0.038^{***}	0.021
	(0.004)	(0.008)	(0.037)
E2	0.011	0.095^{***}	0.035
	(0.011)	(0.025)	(0.132)
Champ	0.093	-1.069	-0.363
	(0.297)	(0.905)	(1.019)
Rain	-0.007^{***}	0.012^{***}	0.001
	(0.002)	(0.004)	(0.017)
$T^{22+}\cdot$ E1	0.012^{**}	-0.001	-0.002
	(0.005)	(0.013)	(0.056)
$T^{22+}\cdot$ E2	0.001	0.030	0.047
	(0.035)	(0.065)	(0.353)
$T^{22+}\cdot$ Champ	0.001	-0.045	-0.026
	(0.016)	(0.040)	(0.277)
Observations	68,390	72,473	14,807
(Pseudo) R^2	0.11	0.08	0.07
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: T^{22+} equals 1 if the observed temperature is higher than 22°. Champ, E1 and E2 stand for the Champions League, second and third highest leagues in the country. *p<0.1; **p<0.05; ***p<0.01.

4.5.4 Robustness checks

To ensure the robustness of the results, several tests have been conducted. First, although temperature bins seem to better capture the temperature effects on soccer productivity (recall the discussion in Subsection 4.4.1), I have estimated the same regression with temperature as a continuous variable. Results presented in Section 4.6 show the same direction and significance of the effects as the regressions using temperature bins. Second, I test an interaction term between temperature and rain to check whether the effects of temperature on soccer productivity are particularly pronounced during matches on rainy days. Since the results in Section 4.6 show that the interaction term between temperature and rain is nonsignificant or zero for all soccer productivity measures, I conclude that the temperature effect is not differentially pronounced on rainy days. As an alternative to the baseline specification, temperature is demeaned by league-specific means and discretized into 9 and 11 bins. The results remain qualitatively unchanged, with stable effect sizes and significance patterns, Table A4.23 and Table A4.24. The same conclusion holds when using home_away team fixed effects (see Table A4.25, Table A4.26, and Table A4.27). To examine whether high-profile matches are systematically scheduled in response to television requirements and therefore correlated with temperature, stadium occupancy, used as a proxy for match salience, is included together with its interaction with temperature. The results in Table A4.22 indicate that the estimated temperature effects are not driven by selectively scheduled top matches. Finally, I conduct a coefficient stability test by (Oster 2019) to address potential unobserved heterogeneity (see Table A4.21). Because all β^* coefficients have the same directional effect as the estimated betas and δ^* is sufficiently large, I argue that unobserved heterogeneity might not significantly impact my results.

4.6 Conclusion

In this paper, I have documented the relationship between temperature and various performance metrics in professional football across ten countries and the Champions League. The findings reveal notable trends. Regarding attacking performance, my analysis indicates a clear enhancement in efficiency under elevated temperature conditions. Teams exhibit a greater propensity to score goals, coupled with improved shot conversion rates and a more effective utilization of set-piece opportunities.

Conversely, the study reveals a decline in defensive performance as temperatures rise. This is evidenced by a reduction in defensive actions, specifically fewer blocked shots, and a greater vulnerability to conceding goals, particularly from set-piece situations. Furthermore, the capacity for maintaining structured play, as reflected in passing accuracy, appears to be negatively impacted by higher temperatures. These results are consistent with heat-related fatigue and loss of concentration, which can reduce defensive effort and passing accuracy, while attacking efficiency increases as defenses tire more quickly.

Moreover, my findings suggest an inverted U-shaped relationship between temperature and player aggression. While aggression, as measured by fouls and yellow cards, tends to increase with rising temperatures up to a certain point, it appears to diminish at the highest heat levels.

Teams originating from colder climatic regions demonstrate a more pronounced decrease in passing volume when competing in warmer conditions. Additionally, the impact of temperature appears to vary across different league levels, with a more substantial increase in fouls observed in lower-tier leagues compared to top divisions. While the Champions League exhibits greater sensitivity in specific areas such as set-piece generation, it generally appears to be less affected by temperature fluctuations overall in the performance indicators analyzed.

From a policy perspective, these findings carry broader implications beyond the domain of professional soccer. First, the evidence that warmer conditions increase match attractiveness and potentially raise spectator attendance points to tangible economic benefits, also for other outdoor sports. Second, the inverted U-shaped pattern in aggressive behavior resonates with insights from behavioral economics, where heat induces more impulsive and emotionally driven decisions. This suggests that policy interventions such as air conditioning in high-stakes environments may mitigate undesirable biases. Third, since football performance depends critically on coordination and collective effort, the observed temperature effects also speak to teamwork in other professional settings. Research on surgical teams highlights the importance of effective collaboration for performance outcomes (Catchpole *et al.* 2008; O'Logbon 2020), suggesting that managing environmental stressors such as heat could play a role in safeguarding productivity and safety in comparable team-based environments.

In conclusion, these findings highlight the influence of temperature on football performance. The observed increase in attacking efficiency under warmer conditions, leading to higher goal productivity, suggests that matches played in elevated temperatures may be more engaging for spectators. Furthermore, the non-linear effects (inverted U-shape relationship) and the varying impact across different leagues emphasize the importance of considering environmental factors when analyzing team performance. It is important to note that climate effects, or global warming, do not appear to be major concerns in this specific context, as the observed effects are primarily related to the immediate impact of temperature during matches. Beyond the described performance effects, football could potentially benefit from increased attendance due to the more attractive nature of matches played in warmer weather.

Appendix

Tables

Table A4.1: Impact of Climatic Origin and Heat on Attacks

	Dependent variable:								
	Poisson			*OLS*					
	Score			Shot conversion			Shot conversion on target		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate	−0.087	0.248	0.001	−0.045	0.248	0.018	−0.073	0.120	0.049
	(0.065)	(0.223)	(0.065)	(0.323)	(1.109)	(0.297)	(0.194)	(0.636)	(0.178)
T^E	−0.015	0.037	0.037	−0.003	0.064	0.014	0.003	0.095	0.035
	(0.031)	(0.035)	(0.032)	(0.153)	(0.174)	(0.150)	(0.092)	(0.100)	(0.090)
Climate $\cdot T^E$	0.045	−0.237	−0.111	−0.035	−0.254	−0.132	−0.065	−0.085	−0.097
	(0.156)	(0.256)	(0.097)	(0.809)	(1.302)	(0.472)	(0.488)	(0.664)	(0.279)
Constant	0.596***	0.790**	0.790***	−2.520**	−2.180	−2.163***	−1.477**	−1.484	−1.289***
	(0.201)	(0.310)	(0.086)	(0.998)	(1.550)	(0.399)	(0.606)	(0.905)	(0.244)
Observations	6,300	6,657	9,275	6,293	6,645	9,269	6,290	6,644	9,263
(Pseudo) R^2	0.10	0.10	0.11	0.12	0.10	0.09	0.10	0.14	0.13
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Climate is defined as a binary variable that takes the value of 1 if the team originates from the 20% coldest cities. T^E equals 1 if the observed temperature falls within the 90th percentile of the temperature distribution. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A4.2: Impact of Climatic Origin and Heat on Attacks

	Poisson			*Poisson*			*OLS*			*OLS*		
	Total shots			Total shots on target			Shooting accuracy			Shot blocking rate		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Climate	−0.018	0.020	−0.101	−0.225	0.109	−0.048	−0.002	0.032	−0.052	−0.021	−0.005	0.008
	(0.022)	(0.068)	(0.517)	(0.348)	(0.117)	(0.034)	(0.011)	(0.035)	(0.159)	(0.230)	(0.030)	(0.010)
T^E	−0.021**	−0.032***	0.323	−0.198	−0.040**	0.015	−0.001	−0.001	−0.005	0.012	0.001	−0.010**
	(0.010)	(0.011)	(0.268)	(0.162)	(0.019)	(0.017)	(0.005)	(0.006)	(0.083)	(0.108)	(0.005)	(0.005)
Climate $\cdot T^E$	0.085*	0.025	−0.091	0.836	−0.117	−0.012	0.005	−0.038	−0.013	−0.002	0.014	−0.009
	(0.051)	(0.067)	(0.798)	(0.827)	(0.129)	(0.051)	(0.027)	(0.036)	(0.248)	(0.546)	(0.037)	(0.014)
Constant	3.148***	3.105***	20.306***	8.167***	2.352***	2.136***	0.363***	0.509***	−0.838***	−1.457**	0.289***	0.213***
	(0.060)	(0.093)	(0.718)	(0.943)	(0.158)	(0.047)	(0.031)	(0.049)	(0.217)	(0.627)	(0.046)	(0.014)
Observations	6,293	6,645	9,269	6,293	6,645	9,269	6,293	6,645	9,269	6,205	5,068	8,212
(Pseudo) R^2	0.10	0.09	0.09	0.14	0.11	0.12	0.11	0.09	0.10	0.12		
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Climate is defined as a binary variable that takes the value of 1 if the team originates from the 20% coldest cities. T^E equals 1 if the observed temperature falls within the 90th percentile of the temperature distribution.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A4.3: Impact of Climatic Origin and Heat on Attacks

	Dependent variable:											
	Poisson			*OLS*			*Poisson*			*OLS*		
	Corners			Corner conversion rate			Free kicks			Free kick conversion rate		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Climate	0.022	−0.041	−0.523*	−0.021	0.282	0.119	−0.426	2.781	0.019	−0.141	0.023	0.001
	(0.036)	(0.099)	(0.310)	(0.032)	(0.722)	(0.181)	(1.280)	(2.849)	(0.022)	(0.495)	(0.021)	(0.008)
T^E	−0.017	−0.040**	0.022	0.003	0.084	0.024	−0.202	−0.650	−0.005	−0.034	0.004	0.005
	(0.017)	(0.017)	(0.161)	(0.015)	(0.105)	(0.092)	(0.600)	(0.469)	(0.011)	(0.236)	(0.003)	(0.004)
Climate $\cdot T^E$	0.052	0.086	−0.347	0.065	−0.381	−0.004	0.575	2.259	−0.038	0.308	−0.018	−0.016
	(0.082)	(0.105)	(0.478)	(0.077)	(0.815)	(0.265)	(2.916)	(3.351)	(0.033)	(1.148)	(0.024)	(0.011)
Constant	2.232***	2.275***	11.003***	0.203**	−1.336	−1.479***	4.608	31.621***	3.593***	−2.351	0.073**	0.063***
	(0.096)	(0.146)	(0.430)	(0.088)	(0.938)	(0.252)	(3.560)	(4.156)	(0.029)	(3.186)	(0.030)	(0.011)
Observations	6,292	6,645	9,268	6,291	6,645	9,268	2,499	5,909	6,280	2,488	5,902	6,279
(Pseudo) R^2	0.10	0.10	0.11	0.09	0.10	0.12	0.13	0.10	0.09	0.08	0.12	0.11
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Climate is defined as a binary variable that takes the value of 1 if the team originates from the 20% coldest cities. T^E equals 1 if the observed temperature falls within the 90th percentile of the temperature distribution. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A4.4: Impact of Climatic Origin and Heat on Aggression

	Dependent variable:								
	Poisson			*Poisson*			*Poisson*		
	Fouls			Yellow cards			Red cards		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate	0.012	−0.004	0.089***	−0.058	−0.244*	0.070*	−0.272	−0.845	0.206
	(0.023)	(0.057)	(0.021)	(0.058)	(0.148)	(0.041)	(0.257)	(0.629)	(0.190)
T^E	−0.019*	0.001	−0.009	−0.031	−0.013	−0.040*	0.069	0.165	0.085
	(0.011)	(0.010)	(0.010)	(0.026)	(0.025)	(0.022)	(0.115)	(0.100)	(0.095)
Climate $\cdot T^E$	−0.026	−0.061	−0.050*	0.031	−0.044	−0.004	−0.007	−0.132	−0.557
	(0.055)	(0.063)	(0.030)	(0.141)	(0.165)	(0.069)	(0.598)	(0.727)	(0.393)
Constant	3.245***	3.046***	3.335***	0.878***	1.707***	1.759***	−3.029***	−0.908	−1.461***
	(0.061)	(0.087)	(0.030)	(0.163)	(0.204)	(0.058)	(1.076)	(0.960)	(0.261)
Observations	6,291	6,622	8,255	6,300	6,657	9,275	6,300	6,657	9,275
(Pseudo) R^2	0.10	0.11	0.13	0.09	0.09	0.13	0.12	0.14	0.13
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Climate is defined as a binary variable that takes the value of 1 if the team originates from the 20% coldest cities. T^E equals 1 if the observed temperature falls within the 90th percentile of the temperature distribution. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A4.5: Regression Results - Aggression (Champions League Teams)

	Dependent variable:		
	Poisson	*Poisson*	*Poisson*
	Fouls	Yellow cards	Red cards
	(1)	(2)	(3)
< 6 °C	0.003	−0.035**	−0.049
	(0.007)	(0.017)	(0.085)
6−10 °C	−0.003	−0.027**	−0.017
	(0.006)	(0.014)	(0.068)
14−18 °C	−0.011*	−0.006	0.024
	(0.006)	(0.014)	(0.069)
18−22 °C	−0.025***	0.005	0.036
	(0.008)	(0.019)	(0.095)
> 22 °C	−0.037***	−0.020	0.010
	(0.011)	(0.026)	(0.131)
Rain	−0.007**	−0.00003	−0.009
	(0.003)	(0.009)	(0.043)
Constant	3.460***	1.433***	0.463
	(0.049)	(0.123)	(0.500)
Observations	15,266	14,952	2,724
(Pseudo) R^2	0.1	0.1	0.1
Home team stadium-by-year FE	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: < 6 °C, 6−10 °C, 14−18 °C, 18−22 °C and > 22 °C stand for temperature bins. 10−14 °C is the omitted category. Rain is a dummy variable for precipitation. Only teams playing Champions League. *p<0.1; **p<0.05; ***p<0.01.

Table A4.6: Regression Results - Attacks (Champions League Teams)

	Dependent variable:		
	Poisson	*OLS*	*OLS*
	Total Score	Score per Shot	Score per Shot on Target
	(1)	(2)	(3)
< 6 °C	−0.046***	−0.004*	−0.010**
	(0.016)	(0.002)	(0.005)
6−10 °C	−0.039***	−0.003*	−0.007*
	(0.015)	(0.002)	(0.004)
14−18 °C	0.006	−0.001	0.003
	(0.015)	(0.002)	(0.004)
18−22 °C	−0.014	−0.005**	−0.002
	(0.018)	(0.002)	(0.005)
> 22 °C	0.028	0.001	0.003
	(0.023)	(0.003)	(0.007)
Rain	0.008	0.0001	0.003
	(0.010)	(0.001)	(0.003)
Constant	2.174***	0.182***	0.443***
	(0.439)	(0.060)	(0.145)
Observations	15,617	15,567	15,567
(Pseudo) R^2	0.11	0.09	0.12
Home team stadium-by-year FE	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: < 6 °C, 6−10 °C, 14−18 °C, 18−22 °C and > 22 °C stand for temperature bins. 10−14 °C is the omitted category. Rain is a dummy variable for precipitation. Only teams playing Champions League. *p<0.1; **p<0.05; ***p<0.01.

Table A4.7: Regression Results - Defense & Possession (Champions League Teams)

	Dependent variable:	
	OLS Passes	*OLS* Passing accuracy
	(1)	(2)
$< 6\,°C$	0.017***	0.002
	(0.002)	(0.005)
6–10 °C	0.007***	0.005
	(0.001)	(0.004)
14–18 °C	−0.010***	0.001
	(0.001)	(0.004)
18–22 °C	−0.018***	−0.013**
	(0.002)	(0.006)
$> 22\,°C$	−0.018***	−0.028***
	(0.003)	(0.008)
Rain	0.005***	0.001
	(0.001)	(0.003)
Constant	6.834***	1.516***
	(0.014)	(0.039)
Observations	7,428	5,211
(Pseudo) R^2	0.10	0.09
Home team stadium-by-year FE	✓	✓
Away team-by-year FE	✓	✓
Referee-by-year FE	✓	✓

Note: $< 6\,°C$, 6–10 °C, 14–18 °C, 18–22 °C and $> 22\,°C$ stand for temperature bins. 10–14 °C is the omitted category. Rain is a dummy variable for precipitation. Only teams playing Champions League. *p<0.1; **p<0.05; ***p<0.01.

Table A4.8: Regression Results - Attacks (Champions League Teams)

	Dependent variable:			
	Poisson		*OLS*	
	Total Shots	Total Shots on Target	Shooting accuracy	Shot blocking rate
	(1)	(2)	(3)	(4)
$< 6\,°$C	−0.007	−0.008	−0.001	−0.001
	(0.007)	(0.011)	(0.004)	(0.003)
6−10 °C	−0.003	−0.011	−0.003	0.004
	(0.006)	(0.009)	(0.003)	(0.003)
14−18 °C	0.011**	0.003	−0.005	−0.002
	(0.006)	(0.009)	(0.003)	(0.003)
18−22 °C	0.025***	−0.010	−0.016***	−0.0003
	(0.008)	(0.013)	(0.005)	(0.004)
$> 22\,°$C	0.035***	0.033*	−0.004	−0.005
	(0.011)	(0.018)	(0.006)	(0.005)
Rain	0.010***	0.0001	−0.004*	0.002
	(0.003)	(0.006)	(0.002)	(0.002)
Constant	3.265***	2.532***	0.497***	0.175***
	(0.065)	(0.104)	(0.037)	(0.037)
Observations	15,567	15,568	15,567	12,035
(Pseudo) R^2	0.10	0.10	0.11	0.09
Home team stadium-by-year FE	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓

Note: $< 6\,°$C, 6−10 °C, 14−18 °C, 18−22 °C and $> 22\,°$C stand for temperature bins. 10−14 °C is the omitted category. Rain is a dummy variable for precipitation. Only teams playing Champions League. *p<0.1; **p<0.05; ***p<0.01.

Table A4.9: Regression Results - Attacks (Champions League Teams)

	Dependent variable:			
	Poisson	*OLS*	*Poisson*	*OLS*
	Corners	Corner conversion rate	Free kicks	Free kick conversion rate
	(1)	(2)	(3)	(4)
$< 6\,°C$	−0.003	−0.010	0.019***	−0.007*
	(0.011)	(0.010)	(0.007)	(0.004)
$6{-}10\,°C$	−0.007	−0.007	0.012**	−0.006**
	(0.009)	(0.008)	(0.006)	(0.003)
$14{-}18\,°C$	0.005	−0.004	−0.004	−0.0003
	(0.009)	(0.008)	(0.006)	(0.003)
$18{-}22\,°C$	0.008	−0.014	−0.021***	0.002
	(0.013)	(0.012)	(0.008)	(0.004)
$> 22\,°C$	0.030*	−0.0003	−0.027**	0.007
	(0.017)	(0.016)	(0.011)	(0.006)
Rain	0.007	−0.001	−0.005	0.003*
	(0.005)	(0.005)	(0.004)	(0.002)
Constant	2.487***	0.269***	3.602***	0.076**
	(0.102)	(0.093)	(0.070)	(0.037)
Observations	15,568	15,568	12,637	12,629
(Pseudo) R^2	0.10	0.11	0.12	0.10
Home team stadium-by-year FE	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓

Note: $< 6\,°C$, $6{-}10\,°C$, $14{-}18\,°C$, $18{-}22\,°C$ and $> 22\,°C$ stand for temperature bins. $10{-}14\,°C$ is the omitted category. Rain is a dummy variable for precipitation. Only teams playing Champions League. *p<0.1; **p<0.05; ***p<0.01.

Robustness checks

Temperature linear trend

Table A4.10: Regression Results - Aggression

	Dependent variable:		
	Poisson	*Poisson*	*Poisson*
	Fouls	Yellow cards	Red cards
	(1)	(2)	(3)
Pass accuracy	-0.721^{***}	-0.459^{***}	0.080
	(0.039)	(0.068)	(0.311)
Temp	0.004^{*}	0.004	0.005
	(0.002)	(0.003)	(0.015)
Rain	0.0001	0.0002	0.001
	(0.0002)	(0.0004)	(0.002)
Pass accuracy · Temp	-0.006^{**}	-0.005	-0.004
	(0.002)	(0.004)	(0.019)
Constant	3.518^{***}	2.141^{***}	-0.055
	(0.073)	(0.126)	(0.701)
Observations	46,655	45,046	8,797
(Pseudo) R^2	0.27	0.18	0.08
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: Pass accuracy is the share of successful passes from the total number of passes. Rain is a dummy variable for precipitation. Temp is a linear temperature variable. *p<0.1; **p<0.05; ***p<0.01.

Table A4.11: Regression Results - Attacks (Linear Temperature)

	Dependent variable:		
	Poisson	*OLS*	*OLS*
	Total Score	Score per Shot	Score per Shot on Target
	(1)	(2)	(3)
Temp	0.004***	0.0003***	0.001***
	(0.001)	(0.0001)	(0.0002)
Rain	0.013***	0.001	0.003**
	(0.005)	(0.001)	(0.001)
Constant	0.682***	0.117***	0.227***
	(0.080)	(0.009)	(0.022)
Observations	75,044	74,915	74,874
(Pseudo) R^2	0.12	0.07	0.05
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. *p<0.1; **p<0.05; ***p<0.01.

Table A4.12: Regression Results - Aggression (Linear Temperature)

	Dependent variable:		
	Poisson	*Poisson*	*Poisson*
	Fouls	Yellow cards	Red cards
	(1)	(2)	(3)
Temp	−0.002***	0.0005	0.002
	(0.0002)	(0.0004)	(0.002)
Rain	−0.006***	0.012***	0.0002
	(0.002)	(0.004)	(0.017)
Constant	3.636***	1.750***	0.243
	(0.061)	(0.147)	(0.846)
Observations	68,390	72,473	14,807
(Pseudo) R^2	0.14	0.09	0.07
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. *p<0.1; **p<0.05; ***p<0.01.

Table A4.13: Regression Results - Defense & Possession (Linear Temperature)

	Dependent variable:	
	Poisson	*OLS*
	Passes	Passing accuracy
	(1)	(2)
Temp	0.022***	0.067***
	(0.00004)	(0.005)
Rain	0.015***	0.043
	(0.0004)	(0.042)
Constant	6.331***	0.226
	(0.006)	(0.724)
Observations	37,870	23,380
(Pseudo) R^2	0.11	0.12
Home team stadium-by-year FE	✓	✓
Away team-by-year FE	✓	✓
Referee-by-year FE	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. *p<0.1; **p<0.05; ***p<0.01.

Table A4.14: Regression Results - Attacks (Linear Temperature)

	Dependent variable:			
	Poisson	*Poisson*	*OLS*	*OLS*
	Total Shots	Total Shots on Target	Shooting accuracy	Shot blocking rate
	(1)	(2)	(3)	(4)
Temp	0.001***	0.0005	−0.0004***	−0.0003***
	(0.0002)	(0.0003)	(0.0001)	(0.0001)
Rain	0.009***	0.005*	−0.001	0.001*
	(0.002)	(0.003)	(0.001)	(0.001)
Constant	2.994***	2.182***	0.481***	0.168***
	(0.025)	(0.042)	(0.014)	(0.017)
Observations	74,915	74,912	74,911	52,532
(Pseudo) R^2	0.16	0.12	0.142	0.086
Home team stadium-by-year FE	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. *p<0.1; **p<0.05; ***p<0.01.

Table A4.15: Regression Results - Attacks (Linear Temperature)

	Dependent variable:			
	Poisson	*OLS*	*Poisson*	*OLS*
	Corners	Corner conversion rate	Free kicks	Free kick conversion rate
	(1)	(2)	(3)	(4)
Temp	0.0002	0.001***	−0.002***	0.0004***
	(0.0003)	(0.0003)	(0.0002)	(0.0001)
Rain	0.013***	−0.001	−0.003	0.002**
	(0.002)	(0.002)	(0.002)	(0.001)
Constant	2.191***	0.279***	1.024***	0.084
	(0.040)	(0.033)	(0.200)	(0.087)
Observations	74,912	74,909	52,352	52,315
(Pseudo) R^2	0.12	0.05	0.18	0.29
Home team stadium-by-year FE	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. *p<0.1; **p<0.05; ***p<0.01.

Temperature interaction term with rain

Table A4.16: Regression Results - Attacks (Temperature and Rain Interaction)

	Dependent variable:		
	Poisson	*OLS*	*OLS*
	Total Score	Score per Shot	Score per Shot on Target
	(1)	(2)	(3)
Temp	0.004***	0.0003***	0.001***
	(0.001)	(0.0001)	(0.0002)
Rain	0.002*	0.0003**	0.001***
	(0.001)	(0.0001)	(0.0003)
Temp · Rain	−0.00003	−0.00001	−0.00003*
	(0.0001)	(0.00001)	(0.00002)
Constant	0.681***	0.117***	0.226***
	(0.080)	(0.009)	(0.022)
Observations	75,044	74,915	74,874
(Pseudo) R^2	0.12	0.07	0.05
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. Temp · Rain denotes an interaction term between temperature and precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table A4.17: Regression Results - Aggression (Temperature and Rain Interaction)

	Dependent variable:		
	Poisson	*Poisson*	*Poisson*
	Fouls	Yellow cards	Red cards
	(1)	(2)	(3)
Temp	-0.002^{***}	0.001	0.002
	(0.0002)	(0.0004)	(0.002)
Rain	-0.001^{***}	0.0001	0.0001
	(0.0003)	(0.001)	(0.004)
Temp · Rain	0.0001^{***}	0.00002	−0.00002
	(0.00002)	(0.0001)	(0.0002)
Constant	3.634^{***}	1.756^{***}	0.244
	(0.061)	(0.147)	(0.846)
Observations	68,390	72,473	14,807
(Pseudo) R^2	0.17	0.16	0.14
Home team stadium-by-year FE	✓	✓	✓
Away team-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. Temp · Rain denotes an interaction term between temperature and precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table A4.18: Regression Results - Defense & Possession (Temperature and Rain Interaction)

	Dependent variable:	
	Poisson	*OLS*
	Passes	Passing accuracy
	(1)	(2)
temp	0.021***	0.064***
	(0.00004)	(0.005)
rain	−0.009***	−0.028***
	(0.0001)	(0.010)
Temp · Rain	0.001***	0.002***
	(0.00000)	(0.001)
Constant	6.334***	0.264
	(0.006)	(0.724)
Observations	37,870	23,380
(Pseudo) R^2	0.16	0.12
Home team stadium-by-year FE	✓	✓
Away team-by-year FE	✓	✓
Referee-by-year FE	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. Temp · Rain denotes an interaction term between temperature and precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table A4.19: Regression Results - Attacks (Temperature and Rain Interaction)

	Dependent variable:			
	Poisson	*Poisson*	*OLS*	*OLS*
	Total Shots	Total Shots on Target	Shooting accuracy	Shot blocking rate
	(1)	(2)	(3)	(4)
Temp	0.001***	0.0003	−0.0004***	−0.0003***
	(0.0002)	(0.0003)	(0.0001)	(0.0001)
Rain	−0.0005	−0.001	−0.0002	0.0003
	(0.0004)	(0.001)	(0.0002)	(0.0002)
Temp · Rain	0.0001***	0.0001**	0.00002	−0.00000
	(0.00002)	(0.00004)	(0.00001)	(0.00001)
Constant	2.995***	2.183***	0.481***	0.168***
	(0.025)	(0.042)	(0.014)	(0.017)
Observations	74,915	74,912	74,911	52,532
(Pseudo) R^2	0.18	1.13	0.14	0.09
Home team stadium-by-year FE	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. Temp · Rain denotes an interaction term between temperature and precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table A4.20: Regression Results - Attacks (Temperature and Rain Interaction)

	Dependent variable:			
	Poisson	*OLS*	*Poisson*	*OLS*
	Corners	Corner conversion rate	Free kicks	Free kick conversion rate
	(1)	(2)	(3)	(4)
Temp	0.0003	0.001***	−0.002***	0.0005***
	(0.0003)	(0.0003)	(0.0002)	(0.0001)
Rain	0.002***	−0.0003	−0.001**	0.0005**
	(0.001)	(0.0005)	(0.0004)	(0.0002)
Temp · Rain	−0.0001	0.00002	0.0001**	−0.00002*
	(0.00003)	(0.00003)	(0.00003)	(0.00001)
Constant	2.189***	0.279***	1.024***	0.084
	(0.040)	(0.033)	(0.200)	(0.087)
Observations	74,912	74,909	52,352	52,315
(Pseudo) R^2	0.14	0.05	0.19	0.29
Home team stadium-by-year FE	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓

Note: Rain is a dummy variable for precipitation. Temp is a linear temperature variable. Temp · Rain denotes an interaction term between temperature and precipitation. *p<0.1; **p<0.05; ***p<0.01.

Table A4.21: Summary of Oster robustness checks for selected variables

Variable	β^*	δ^*
Total Score	60.09	1.365
Score per Shot	8.339	1.171
Score per Shot on Target	10.970	0.470
Total Shots	82.7	1.257
Total Shots on Target	15.6	1.106
Shooting Accuracy	-7.697	1.258
Corners	-2141	1.140
Corner Conversion Rate	15.50	1.166
Free Kicks	-6.57	1.649
Free Kicks Conversion Rate	5.87	1.444
Shot blocking rate	-4.103	0.589
Passes	6410	0.659
Passing Accuracy	12.10	0.757
Fouls	-80.17	0.649
Yellow cards	-40.38	1.473
Red cards	20.84	0.644

Note: Max R^2 is set to 0.9 and beta hat to 0, by default.

Table A4.22: Weather, stadium occupancy and match statistics

	Total Shots	Shots on Target	Shooting accuracy	Corners	Corner conv.	Free kicks	FK conv.	Passes	Pass acc.	Shot block rate	Fouls	Yellow cards	Red cards
Intercept	3.022***	2.192***	0.470***	2.328***	0.212**	3.558***	0.034	4.709***	-4.624	0.105	3.835***	1.890***	0.084
	(0.064)	(0.110)	(0.034)	(0.096)	(0.082)	(0.165)	(0.077)	(0.036)	(2.988)	(0.081)	(0.065)	(0.158)	(0.903)
Temperature	0.0004	-0.0012	-0.0007***	0.0007	0.0003	-0.0009*	0.0004*	-0.0174***	-0.0592***	-0.0002	-0.0012***	-0.0008	-0.0018
	(0.0004)	(0.0007)	(0.0002)	(0.0007)	(0.0006)	(0.0005)	(0.0002)	(0.0001)	(0.0110)	(0.0002)	(0.0004)	(0.0010)	(0.0047)
Stadium occupancy	-0.0002	-0.0563***	-0.0244***	-0.0149	-0.0078	-0.0207*	0.0001	-0.1404***	0.1050	0.0050	-0.0027	0.0108	-0.0056
	(0.0097)	(0.0158)	(0.0054)	(0.0151)	(0.0129)	(0.0107)	(0.0051)	(0.0022)	(0.2600)	(0.0056)	(0.0100)	(0.0235)	(0.1137)
Temp × occupancy	0.0013	0.0019	0.0003	-0.0000	0.0002	-0.0006	-0.0001	0.0284	0.0712	0.0001	-0.0005	0.0005	0.0025
	(0.0016)	(0.0029)	(0.0003)	(0.0009)	(0.0007)	(0.0006)	(0.0303)	(0.0691)	(0.0138)	(0.0003)	(0.0006)	(0.0013)	(0.0063)
Rain	0.0092***	0.0040	-0.0023**	0.0120***	-0.0000	-0.0026	0.0018*	0.0084***	0.0333	0.0028***	-0.0071***	0.0071	0.0038
	(0.0019)	(0.0031)	(0.0011)	(0.0030)	(0.0025)	(0.0021)	(0.0010)	(0.0004)	(0.0456)	(0.0010)	(0.0019)	(0.0045)	(0.0211)

Table A4.23: Effects of Temperature Quantiles and Rain on Match Statistics

	Total Shots	Shots on Target	Shooting Acc.	Corners	Corner Conv.	Free Kicks	FK Conv.	Passes	Pass Acc.	Shot Block.	Fouls	Yellow Cards	Red Cards
Temp bin 1	-0.013***	-0.012***	0.007***	-0.036***	-0.002*	-0.144***	-0.539***	0.143***	0.539***	0.002	0.007**	-0.022***	-0.008
	(0.003)	(0.003)	(0.002)	(0.010)	(0.001)	(0.001)	(0.084)	(0.001)	(0.084)	(0.002)	(0.003)	(0.007)	(0.033)
Temp bin 2	-0.003	-0.008***	0.003	-0.022**	-0.002*	-0.033***	-0.209***	0.033***	0.209***	0.001	0.004	-0.008	-0.004
	(0.003)	(0.003)	(0.002)	(0.009)	(0.001)	(0.001)	(0.077)	(0.001)	(0.077)	(0.002)	(0.003)	(0.007)	(0.031)
Temp bin 3	0.001	-0.001	0.001	-0.003	0.000	-0.003***	-0.086	0.003***	0.086	0.001	0.001	-0.005	-0.007
	(0.003)	(0.002)	(0.002)	(0.009)	(0.001)	(0.001)	(0.075)	(0.001)	(0.075)	(0.002)	(0.003)	(0.007)	(0.030)
Temp bin 5	0.002	0.003	-0.000	0.008	0.001	0.133***	0.362***	-0.133***	-0.362***	0.000	-0.006**	-0.004	0.016
	(0.003)	(0.003)	(0.002)	(0.009)	(0.001)	(0.001)	(0.075)	(0.001)	(0.075)	(0.002)	(0.003)	(0.007)	(0.030)
Temp bin 6	0.009***	0.008***	-0.003*	0.024***	0.001	0.174***	0.464***	-0.174***	-0.464***	-0.003**	-0.009***	-0.002	0.009
	(0.003)	(0.003)	(0.002)	(0.009)	(0.001)	(0.001)	(0.078)	(0.001)	(0.078)	(0.002)	(0.003)	(0.007)	(0.032)
Temp bin 7	0.016***	0.006**	-0.000	0.039***	0.002	0.288***	0.738***	-0.288***	-0.738***	-0.004**	-0.017***	-0.001	0.016
	(0.003)	(0.003)	(0.002)	(0.010)	(0.001)	(0.001)	(0.086)	(0.001)	(0.086)	(0.002)	(0.003)	(0.008)	(0.035)
Rain	0.008***	0.003**	-0.001	0.013***	0.001	0.017***	0.039	-0.017***	-0.039	0.001	-0.006***	0.011***	0.000
	(0.002)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.042)	(0.000)	(0.042)	(0.001)	(0.002)	(0.004)	(0.017)

Table A4.24: Effects of Temperature Quantiles and Rain on Match Statistics

	Total Shots	Total Shots on Target	Shooting accuracy	Corners	Corner conv.	Free kicks	FK conv.	Passes	Pass acc.	Shot block rate	Fouls	Yellow cards	Red cards
Temp bin 1	-0.0149***	-0.0002	0.0075***	-0.0361***	-0.0020	-0.0128***	-0.0020	0.1509***	0.5865***	0.0026	0.0108***	-0.0152*	-0.0207
	(0.0039)	(0.0064)	(0.0022)	(0.0118)	(0.0014)	(0.0048)	(0.0016)	(0.0009)	(0.1035)	(0.0021)	(0.0038)	(0.0091)	(0.0406)
Temp bin 2	-0.0075**	0.0027	0.0051**	-0.0277**	-0.0018	-0.0104***	-0.0018	0.1538***	0.5213***	0.0008	0.0009	-0.0166*	-0.0230
	(0.0037)	(0.0061)	(0.0021)	(0.0112)	(0.0013)	(0.0046)	(0.0016)	(0.0009)	(0.0976)	(0.0020)	(0.0037)	(0.0087)	(0.0387)
Temp bin 3	-0.0029	-0.0050	0.0001	-0.0310**	-0.0032**	-0.0097***	-0.0032**	0.0226***	0.2006**	0.0023	0.0040	-0.0069	-0.0261
	(0.0036)	(0.0060)	(0.0021)	(0.0110)	(0.0013)	(0.0045)	(0.0015)	(0.0008)	(0.0952)	(0.0020)	(0.0036)	(0.0085)	(0.0378)
Temp bin 4	0.0006	-0.0016	-0.0004	-0.0021	-0.0003	-0.0006	-0.0003	0.0151***	0.1308	0.0019	-0.0010	-0.0084	-0.0178
	(0.0036)	(0.0059)	(0.0021)	(0.0107)	(0.0013)	(0.0044)	(0.0015)	(0.0008)	(0.0951)	(0.0019)	(0.0035)	(0.0084)	(0.0375)
Temp bin 5	0.0013	-0.0007	0.0007	-0.0041	-0.0004	-0.0012	-0.0004	0.0315***	0.1328	0.0009	0.0013	-0.0012	-0.0212
	(0.0036)	(0.0058)	(0.0020)	(0.0107)	(0.0013)	(0.0044)	(0.0015)	(0.0008)	(0.0929)	(0.0019)	(0.0035)	(0.0083)	(0.0373)
Temp bin 7	0.0002	-0.0033	-0.0010	0.0046	0.0005	0.0013	0.0005	-0.0824***	-0.2077**	0.0026	-0.0073**	-0.0078	-0.0144
	(0.0036)	(0.0059)	(0.0020)	(0.0107)	(0.0013)	(0.0044)	(0.0015)	(0.0008)	(0.0920)	(0.0019)	(0.0035)	(0.0084)	(0.0377)
Temp bin 8	0.0065*	-0.0015	-0.0031	0.0065	-0.0005	0.0028	-0.0005	-0.1026***	-0.2952***	-0.0007	-0.0040	0.0007	0.0035
	(0.0036)	(0.0059)	(0.0021)	(0.0109)	(0.0013)	(0.0045)	(0.0015)	(0.0008)	(0.0937)	(0.0019)	(0.0036)	(0.0085)	(0.0381)
Temp bin 9	0.0095**	0.0010	-0.0031	0.0254**	0.0012	0.0074**	0.0012	-0.1608***	-0.4359***	-0.0035*	-0.0078**	-0.0007	0.0017
	(0.0037)	(0.0061)	(0.0021)	(0.0111)	(0.0013)	(0.0045)	(0.0015)	(0.0009)	(0.0961)	(0.0020)	(0.0037)	(0.0087)	(0.0387)
Temp bin 10	0.0185***	0.0100	-0.0036*	0.0348***	0.0012	0.0073**	0.0012	-0.2391***	-0.5849***	-0.0021	-0.0162***	-0.0014	-0.0138
	(0.0038)	(0.0063)	(0.0022)	(0.0115)	(0.0014)	(0.0046)	(0.0015)	(0.0009)	(0.0975)	(0.0021)	(0.0038)	(0.0089)	(0.0396)
Temp bin 11	0.0106**	0.0094	-0.0007	0.0409***	0.0024	0.0077**	0.0024	-0.2634***	-0.6802***	-0.0050**	-0.0198***	-0.0043	0.0059
	(0.0041)	(0.0068)	(0.0024)	(0.0125)	(0.0015)	(0.0048)	(0.0016)	(0.0009)	(0.1043)	(0.0022)	(0.0041)	(0.0096)	(0.0423)
Rain	0.0082***	0.0053**	-0.0009	0.0130***	0.0007	0.0029**	0.0007	-0.0171***	-0.0391	0.0013	-0.0061***	0.0112***	0.0003
	(0.0016)	(0.0026)	(0.0009)	(0.0048)	(0.0006)	(0.0014)	(0.0006)	(0.0004)	(0.0419)	(0.0009)	(0.0016)	(0.0037)	(0.0169)

Table A4.25: Home_Away Team Fixed Effects

	Passes	Pass Accuracy	Fouls	Yellow Cards	Red Cards
Temp bin 1	-0.0123***	-0.0937	0.0098*	-0.0239*	-0.0245
	(0.0011)	(0.1289)	(0.0040)	(0.0095)	(0.0675)
Temp bin 2	0.0770***	0.1600	0.0095*	-0.0118	-0.0508
	(0.0010)	(0.1252)	(0.0039)	(0.0092)	(0.0645)
Temp bin 3	0.0385***	0.0928	0.0024	-0.0029	-0.0267
	(0.0010)	(0.1236)	(0.0039)	(0.0091)	(0.0647)
Temp bin 5	0.0792***	0.2140.	-0.0065.	-0.0066	0.0002
	(0.0010)	(0.1212)	(0.0039)	(0.0091)	(0.0654)
Temp bin 6	0.0086***	0.0656	-0.0056	0.0005	-0.0264
	(0.0010)	(0.1219)	(0.0039)	(0.0092)	(0.0653)
Temp bin 7	0.1063***	0.2646*	-0.0141***	0.0039	0.0159
	(0.0010)	(0.1223)	(0.0040)	(0.0094)	(0.0667)
Rain	0.0605***	0.1487*	-0.0100***	0.0030	-0.0016
	(0.0006)	(0.0688)	(0.0022)	(0.0051)	(0.0361)
Home_Away Team FE	Yes	Yes	Yes	Yes	Yes
Observations	31,343	16,704	59,704	63,675	7,927

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.26: Home_Away Team Fixed Effects

	Total Shots	Shots on Target	Shot Accuracy	Blocked Shots	Shot Conversion	Shot Conversion Target
Temp bin 1	-0.0169***	-0.0027	0.0076***	0.0007	-0.0011	-0.0104***
	(0.0040)	(0.0065)	(0.0020)	(0.0019)	(0.0012)	(0.0030)
Temp bin 2	-0.0060	-0.0018	0.0030	0.0005	-0.0011	-0.0067*
	(0.0039)	(0.0064)	(0.0020)	(0.0019)	(0.0012)	(0.0030)
Temp bin 3	0.0012	0.0038	0.0020	0.0012	0.0003	-0.0006
	(0.0038)	(0.0063)	(0.0020)	(0.0019)	(0.0012)	(0.0030)
Temp bin 5	0.0053	0.0089	0.0012	-0.0018	0.0010	0.0028
	(0.0038)	(0.0063)	(0.0020)	(0.0019)	(0.0012)	(0.0030)
Temp bin 6	0.0116**	0.0086	-0.0012	-0.0039*	0.0012	0.0063*
	(0.0039)	(0.0064)	(0.0020)	(0.0019)	(0.0012)	(0.0030)
Temp bin 7	0.0112**	0.0096	-0.0011	-0.0038.	0.0011	0.0040
	(0.0040)	(0.0066)	(0.0021)	(0.0020)	(0.0012)	(0.0031)
Rain	0.0091***	0.0035	-0.0018.	0.0021*	0.0011	0.0043**
	(0.0021)	(0.0035)	(0.0011)	(0.0011)	(0.0007)	(0.0016)
Home_Away Team FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,088	66,084	66,082	44,550	66,088	66,048

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.27: Home_Away Team Fixed Effects

	Corners	Corner Conversion	Free Kicks	FK Conversion	Total Score
Temp bin 1	-0.0154*	-0.0046	0.0156***	-0.0041*	-0.0308*
	(0.0061)	(0.0046)	(0.0046)	(0.0017)	(0.0120)
Temp bin 2	-0.0071	-0.0025	0.0167***	-0.0029.	-0.0188
	(0.0060)	(0.0045)	(0.0045)	(0.0017)	(0.0117)
Temp bin 3	-0.0100.	0.0043	0.0125**	-0.0001	0.0006
	(0.0060)	(0.0045)	(0.0044)	(0.0017)	(0.0116)
Temp bin 5	-0.0047	0.0075.	0.0020	0.0010	0.0160
	(0.0060)	(0.0045)	(0.0044)	(0.0017)	(0.0115)
Temp bin 6	-0.0061	0.0106*	-0.0009	0.0020	0.0255*
	(0.0061)	(0.0046)	(0.0045)	(0.0017)	(0.0117)
Temp bin 7	-0.0101	0.0069	-0.0163***	0.0044*	0.0236*
	(0.0062)	(0.0047)	(0.0046)	(0.0017)	(0.0119)
Rain	0.0104**	0.0012	-0.0091***	0.0026**	0.0161*
	(0.0033)	(0.0025)	(0.0025)	(0.0009)	(0.0064)
Home_Away Team FE	Yes	Yes	Yes	Yes	Yes
Observations	66,085	66,082	43,554	43,520	66,091

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.28: Weather statistics within countries and leagues

Country	Temperature in °C			Precipitation in mm		
	min	mean	max	min	mean	max
Champions league	7.59	11.7	15.79	1.16	1.61	2.25
UK	7.61	9.07	10.54	1.68	2.55	3.99
Germany	7.45	9.33	10.85	1.11	1.97	2.97
Spain	6.83	14.2	19.68	0.52	2.03	4.98
Italy	10.19	13.12	18.56	1.13	3.04	5.76
Portugal	12.68	14.45	17.65	0.46	3.5	5.98
France	9.33	11.55	16.05	1.55	2.38	4.15
Netherlands	9.05	9.53	9.98	1.69	2.38	3.13
Brazil	16.08	21.5	28.02	1.37	2.91	5.98
Argentina	14.16	17.63	19.57	0.74	2.53	4.68
USA	13.32	17.59	24.27	0.26	3.12	6.45

Note:

Table A4.29: Data availability among leagues – Part 1

Country	League	Score	Fouls	Yellow cards	Red cards	Total shots	Shots on target
Europe	Champions League	Y	Y	Y	Y	Y	Y
UK	E0	Y	Y	Y	Y	Y	Y
UK	E1	Y	Y	Y	Y	Y	Y
UK	E2	Y	Y	Y	Y	Y	Y
Germany	E0	Y	Y	Y	Y	Y	Y
Germany	E1	Y	Y	Y	Y	Y	Y
Germany	E2	Y	Y	Y	Y	Y	Y
Spain	E0	Y	Y	Y	Y	Y	Y
Spain	E1	Y	Y	Y	Y	Y	Y
Italy	E0	Y	Y	Y	Y	Y	Y
Italy	E1	Y	Y	Y	Y	Y	Y
Portugal	E0	Y	Y	Y	Y	Y	Y
Portugal	E1	Y	Y	Y	Y	Y	Y
France	E0	Y	Y	Y	Y	Y	Y
France	E1	Y	Y	Y	Y	Y	Y
Netherlands	E0	Y	Y	Y	Y	Y	Y
Netherlands	E1	Y	Y	Y	Y	Y	Y
Brazil	E0	Y	Y	Y	Y	Y	Y
Brazil	E1	Y	Y	Y	Y	Y	Y
Argentina	E0	Y	Y	Y	Y	Y	Y
Argentina	E1	Y	Y	Y	Y	Y	Y
USA	E0	Y	Y	Y	Y	Y	Y
USA	E1	Y	Y	Y	Y	Y	Y

Note: Y = available, N = not available. E0, E1 and E2 stand for the top, second and third highest leagues in the country, respectively.

Table A4.30: Data availability among leagues – Part 2

Country	League	Blocked shots	Corners	Free kicks	Passes	Successful passes
Europe	Champions League	Y	Y	Y	Y	Y
UK	E0	Y	Y	Y	Y	Y
UK	E1	Y	Y	Y	Y	Y
UK	E2	Y	Y	Y	Y	Y
Germany	E0	Y	Y	Y	Y	Y
Germany	E1	Y	Y	Y	Y	Y
Germany	E2	Y	Y	Y	N	N
Spain	E0	Y	Y	Y	Y	Y
Spain	E1	Y	Y	Y	Y	Y
Italy	E0	Y	Y	Y	Y	Y
Italy	E1	Y	Y	Y	Y	Y
Portugal	E0	Y	Y	Y	Y	Y
Portugal	E1	Y	Y	Y	N	N
France	E0	Y	Y	Y	Y	Y
France	E1	Y	Y	Y	Y	Y
Netherlands	E0	Y	Y	Y	Y	Y
Netherlands	E1	Y	Y	Y	Y	Y
Brazil	E0	Y	Y	Y	Y	Y
Brazil	E1	Y	Y	Y	Y	Y
Argentina	E0	Y	Y	Y	Y	Y
Argentina	E1	Y	Y	Y	Y	Y
USA	E0	Y	Y	Y	Y	Y
USA	E1	Y	Y	Y	Y	Y

Note: Y = available, N = not available. E0, E1 and E2 stand for the top, second and third highest leagues in the country, respectively.

Table A4.31: Summary statistics (Part 1)

Country	Total number of passes	Yellow cards	Red cards	Total number of fouls	Total shots	Total shots on target
Champions League	1007.30	4.17	1.03	26.75	24.91	9.68
UK	824.24	3.60	1.00	22.07	24.26	8.20
Germany	847.88	4.14	1.00	26.52	24.77	9.54
Spain	816.99	5.17	1.06	27.71	22.54	7.95
Italy	836.85	4.90	1.09	28.44	23.46	8.88
Portugal	801.83	5.31	1.11	30.94	21.93	8.33
France	878.46	3.74	1.09	26.31	22.62	8.21
Netherlands	879.78	3.21	1.00	22.08	24.63	10.01
Brazil	836.44	4.84	1.11	29.96	24.42	8.24
Argentina	765.30	5.01	1.13	26.53	23.71	8.07
USA	873.29	4.03	1.05	24.74	25.20	8.91

Table A4.32: Summary statistics (Part 2)

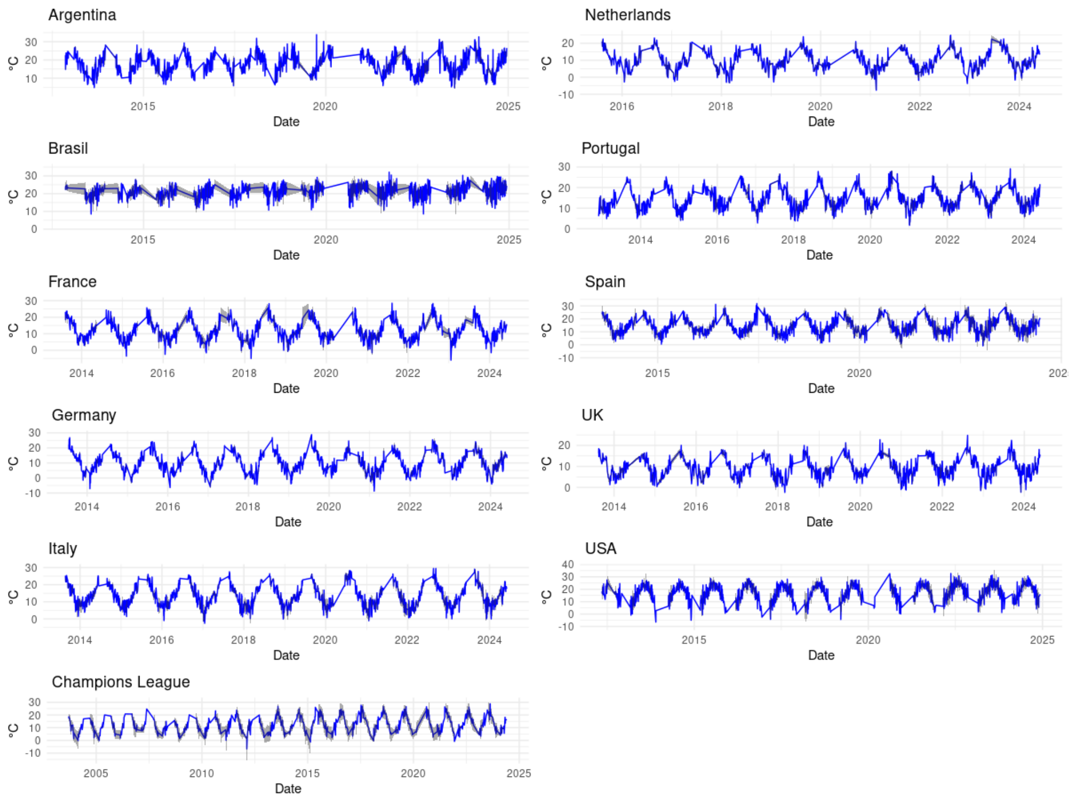
Country	Blocked shots / Total shots	Total number of corners	Score / Corners	Total number of free kicks	Score / Free kicks	Score
Champions League	0.21	9.65	0.29	28.60	0.10	2.68
UK	0.27	10.10	0.27	24.26	0.11	2.58
Germany	0.23	9.77	0.30	28.16	0.11	2.80
Spain	0.23	9.47	0.26	31.37	0.08	2.32
Italy	0.25	9.90	0.27	33.02	0.08	2.49
Portugal	0.23	10.34	0.25	33.42	0.08	2.46
France	0.23	9.23	0.28	30.04	0.09	2.44
Netherlands	0.24	10.07	0.32	25.63	0.12	3.02
Brazil	0.23	10.33	0.23	32.99	0.07	2.21
Argentina	0.22	9.39	0.24	25.53	0.08	2.18
USA	0.24	9.74	0.30	27.78	0.11	2.79

Table A4.33: Summary statistics (Part 3)

Country	Score / Total shots	Score / Shots on target
Champions League	0.11	0.28
UK	0.11	0.32
Germany	0.12	0.30
Spain	0.10	0.30
Italy	0.11	0.29
Portugal	0.11	0.30
France	0.11	0.30
Netherlands	0.13	0.31
Brazil	0.09	0.27
Argentina	0.09	0.27
USA	0.11	0.32

Graphs

Figure A4.1: Temperature deviations from the mean.



To illustrate, c

Other

Consider a model in which match-level productivity P is a function of attacking quality $A(t,x)$ and defensive quality $D(t,x)$, both depending on temperature t and on other variables x:

$$P = P(A(t,x), D(t,x))$$

Taking the derivative with respect to temperature, we obtain:

$$\frac{dP}{dt} = \frac{\partial P}{\partial A} \cdot \frac{dA}{dt} + \frac{\partial P}{\partial D} \cdot \frac{dD}{dt}$$

This expression shows that any observed change in productivity with temperature ($\frac{dP}{dt}$) could be due to changes in attacking performance, defensive performance, or both. Moreover, attackers and defenders might both improve or both

Figure A4.2: Temperature effects on fouls and goals.

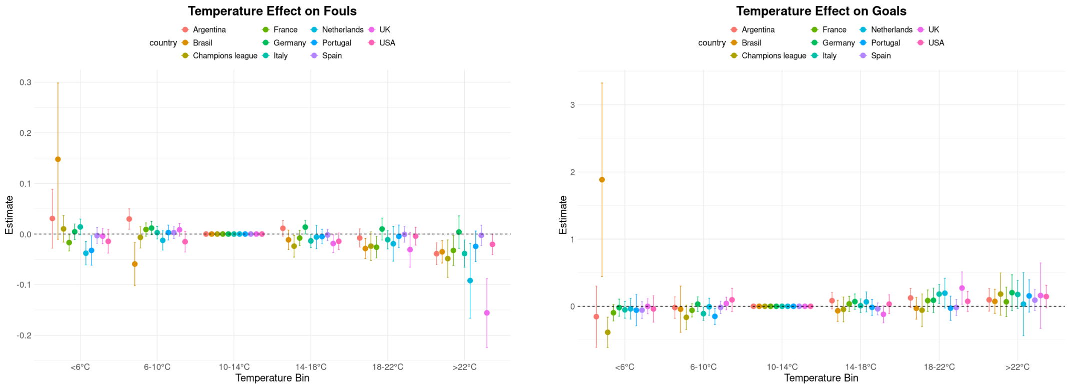
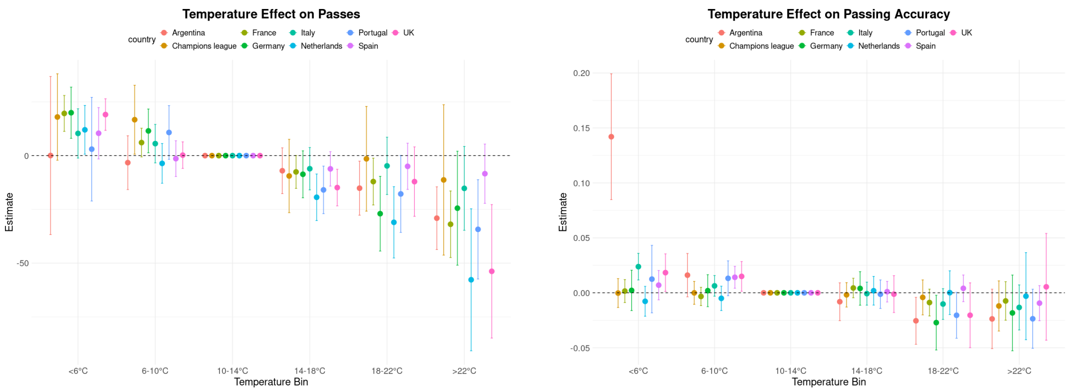


Figure A4.3: Temperature effects on passing.



deteriorate under certain conditions - what matters is the relative magnitude of those changes.

Figure A4.4: Temperature effects on shooting.

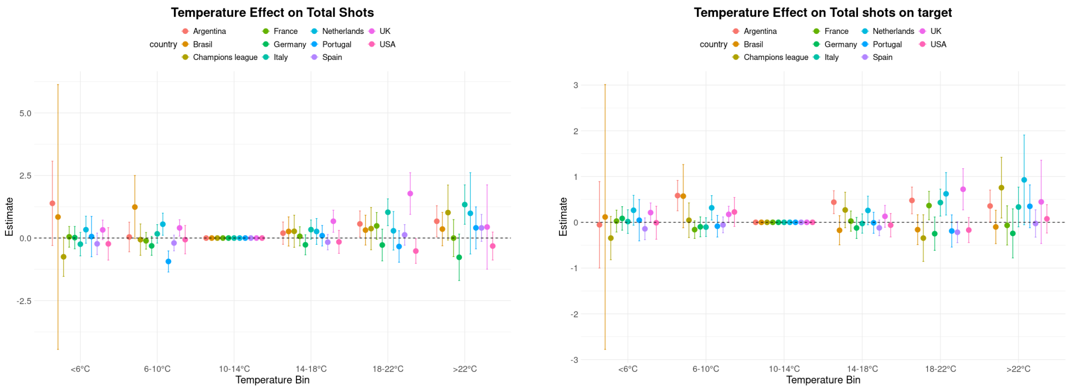


Figure A4.5: Temperature effects on shot accuracy and blocking.

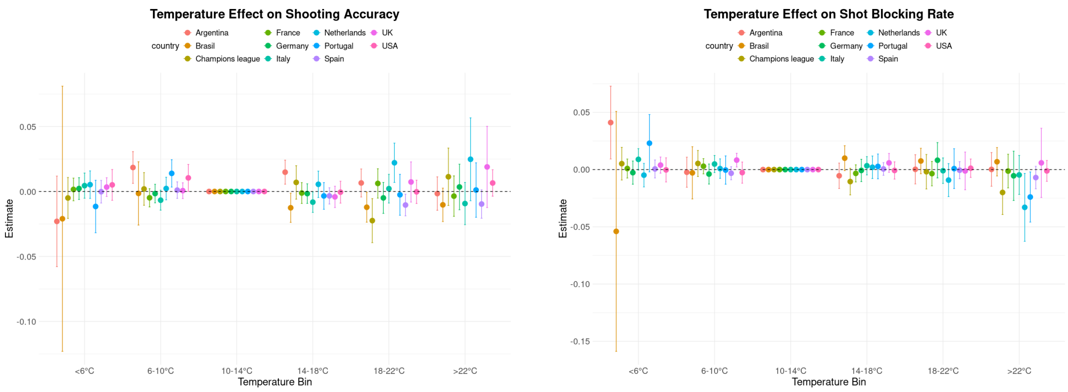


Figure A4.6: Temperature effects on goal conversion.

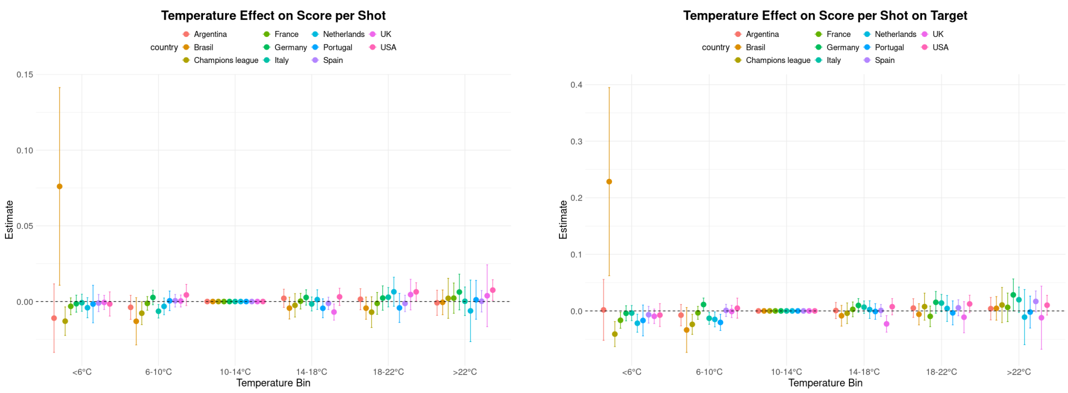


Figure A4.7: Temperature effects on free kicks.

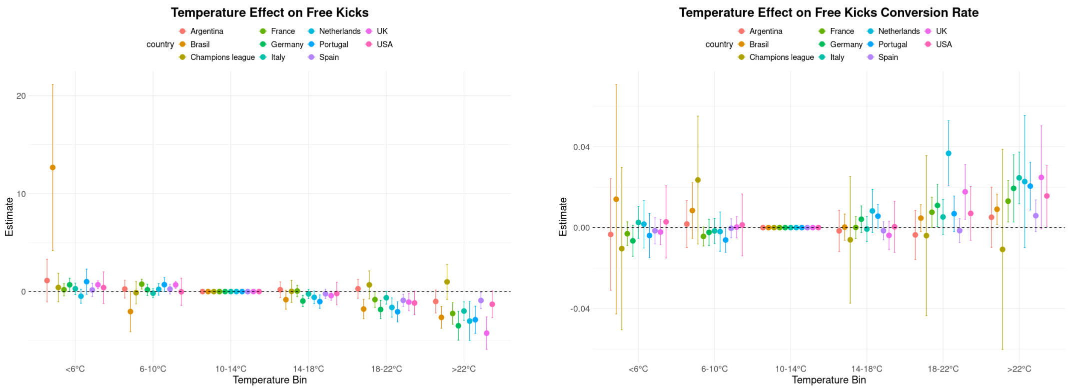


Figure A4.8: Temperature effects on corners.

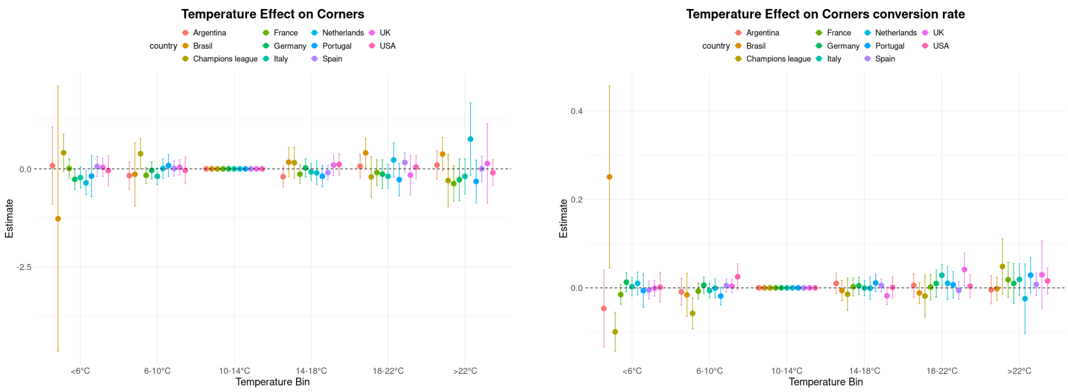


Figure A4.9: Temperature effects on cards.

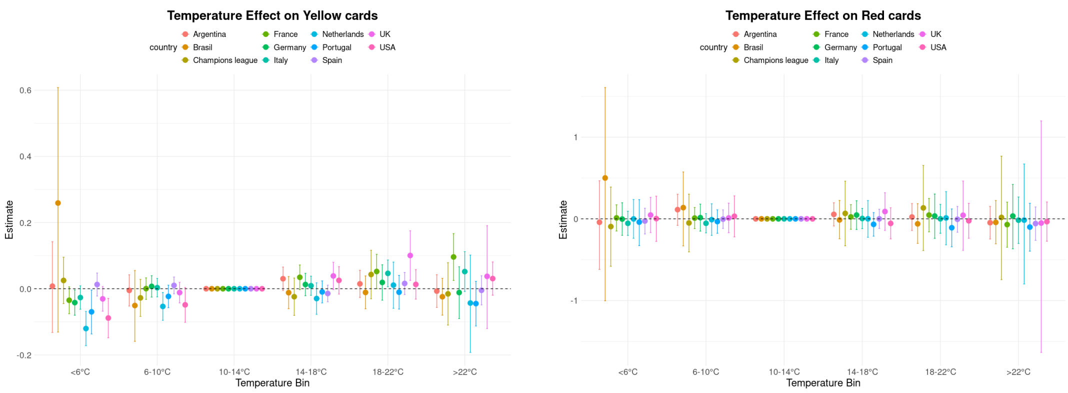
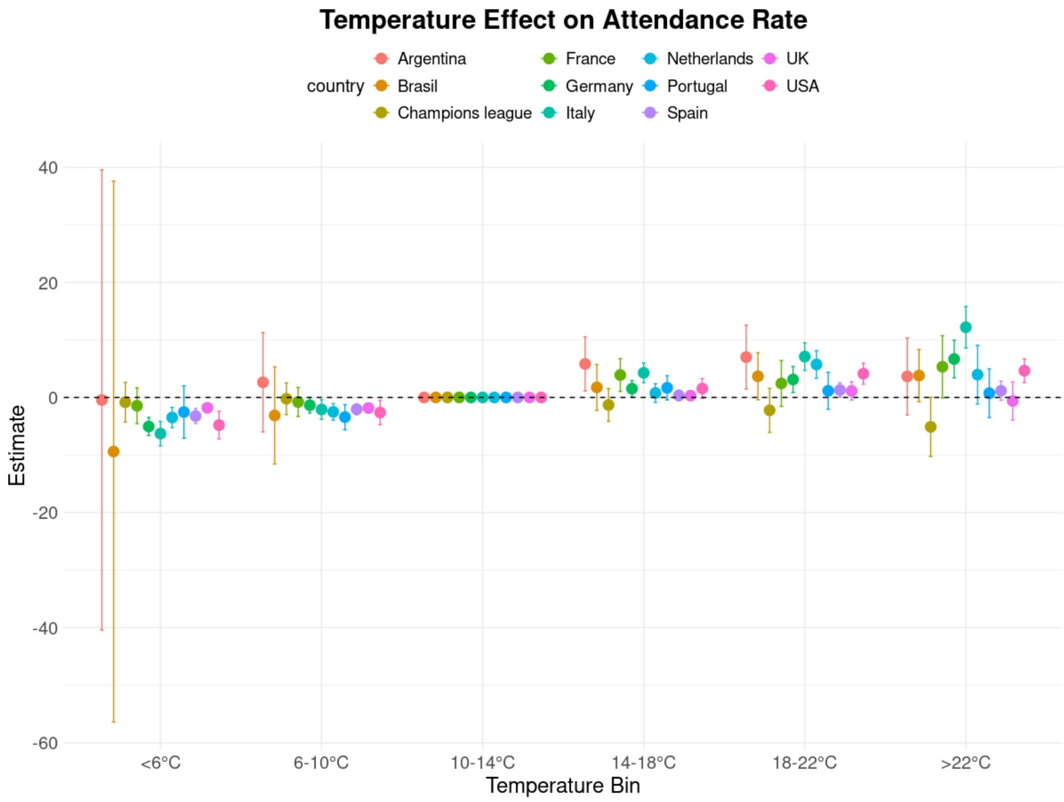


Figure A4.10: Temperature effect on attendance.



Chapter 5

Conclusion

The dissertation investigates how weather shapes human behavior, with a particular focus on crime and productivity. Understanding these links is crucial, as climate change is expected to alter temperature and precipitation patterns worldwide, potentially amplifying their economic and social consequences.

The first essay synthesizes global evidence on the temperature–homicide relationship through a meta-analysis of 156 estimates from 20 studies. It shows that the positive association widely reported in the literature is largely driven by publication bias, and that the corrected mean effect is statistically insignificant. This finding challenges the prevailing view that high temperatures necessarily lead to higher homicide rates.

The second essay uses original daily crime data from the Czech Republic and documents short-term effects of weather on crime. Warmer temperatures increase most crime categories (except homicides), precipitation reduces crime, and alcohol use partially mediates these effects. These results underline the role of situational factors in criminal behavior and suggest that deterrence and policing strategies should account for temperature-related and alcohol-mediated effects, for instance by strengthening law enforcement and regulating alcohol availability during hot periods and large public events.

The third essay investigates weather effects on human productivity using professional soccer data. It finds that warmer conditions improve attacking efficiency but weaken defensive performance, with fouls exhibiting an inverted U-shaped pattern. These results show that temperature fluctuations can affect individual and collective output in high-stakes, competitive environments.

Together, the three essays provide a comprehensive perspective on how weather influences human behavior, combining meta-analytic evidence, administrative crime records, and performance data from professional sports. They contribute to the literature by clarifying the magnitude of temperature effects and illustrating behavioral responses outside of traditional economic settings. The findings also show that weather effects are not uniform: in some contexts they are negligible, in others they may have adverse social consequences—such as increased crime—while in some cases, like soccer performance, they can even be beneficial. This complexity underscores that the behavioral consequences of weather are context-dependent rather than universally adverse.

Future research could extend this work by examining the role of air pollution as an additional environmental factor shaping behavior, or by moving toward health economics to explore how weather and environmental variables jointly affect health, mortality, and health-related productivity. Such research would further inform policies aimed at mitigating the social costs of environmental change.

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Appendix A

Response to Opponents

A.1 Prof. Ming-Jen Lin Ph.D.

The topics discussed in this paper are generally interesting, particularly the second essay which makes use of panel data of crime convictions and temperature records in Czech Republic. The three essays also complement each other in the sense that they investigate academic, social and behavior outcomes brought by weather conditions. Nevertheless, I personally find this paper difficult to navigate. The readability of the paper would be significantly improved by rewriting several paragraphs, changing the structure of the paper and using more constructive and specific vocabularies. In addition, some major concerns and issues remain unsolved in the empirical methodologies. But overall, the thesis can be defended after revision indicated in my comments.

Summary

The paper consists of three essays. All three essays focus on how human behaviors are affected by weather conditions. The first essay approaches this issue by meta-analysis. The author collects estimate of the marginal effect of one Celsius degree increase in temperature has on homicide rate in different countries from roughly 20 published research papers. After adjusting for publication bias, the author finds that there is no general effect of temperature on homicide. Next, the second essay leverages the panel data of crime rate in multiple regions in Czech Republic. Using fixed effect models, the author reveals the positive relation between temperature and crime rate and the negative relation between precipitation and crime rate.Assault, theft, and robbery reflects an inverted U-shape relationship with In conclusion, the three essays complement each other as they characterize the effect of temperature on human behaviors from different aspects. The author also calls for more research on the effect of environment change on health economy and human behaviors.

Comments

Essay 1

- The author chooses linear regression and Bayesian model average approaches for metaanalysis, but comparison between the two are not in the same narrative framework. The author should have thoroughly discussed the advantages and disadvantages of the methodologies under the same framework.

> ***Author reply:***
>
> *Linear regression serves as a frequentist robustness check to the BMA approach, as recommended by the meta-analysis guidelines in economics (see Havránek* et al. *(2020) and Irsova* et al. *(2024)). I have addressed this comment in the following sentence in the thesis:*
> *"Bayesian model averaging with a dilution prior is employed as the main tool to address both model uncertainty and collinearity among study characteristics, in line with recent guidelines for meta-analysis in economics Havránek* et al. *(2020); Irsova* et al. *(2024). In addition, a linear regression model is estimated as a frequentist benchmark, which serves to verify that the qualitative conclusions are not driven by the Bayesian framework but remain robust across different inferential approaches.", page 21*

- The author claims that the result is robust by controlling data characteristics, structural variation, estimation methods, spatial and publication characteristics, but there is no systematic discussion about how these factors affect estimates besides regression tables. The author could have explained the reasons to include these factors and discussed how different factors interact and the mechanisms affecting the final conclusion of this essay in depth.

> ***Author reply:***
>
> *I have added a new paragraph in the thesis addressing your comment in more detail:*
> *"The considered types of heterogeneity capture distinct mechanisms through which temperature effects on homicide rates may vary across studies. Data characteristics reflect the degree of temporal aggregation and thus*

the ability to identify responses of homicide rates to temperature. Structural variation accounts for non-linearities and correlated weather variables, which can attenuate estimated effects. Spatial characteristics proxy for institutional and climatic contexts that condition the temperature–homicides relationship. Finally, publication characteristics capture systematic differences in reported estimates: high-impact journals may favor studies with stronger or more significant effects, while regressions based on very large samples might produce different effect estimates than those based on smaller samples.", page 19

Essay 2

- The author has not addressed or justified the endogeneity problem. For instance, can business cycle be a omitted variable that should have be included in the regression as a control variable? Can there be event effect, weekend effect or the effect of police deployment? Without justification for exogeneity or causal inference strategy, the empirical result of this essay can only be correlation but causal relation.

Author reply:

Since my identification strategy relies on daily changes in crime and weather, I do not expect business cycle variables to cause an endogeneity problem. I explain this briefly in the corresponding section of Chapter 3: "The identifying variation comes from within-district, day-to-day fluctuations in weather, which are plausibly exogenous to short-run changes in economic activity and other socio-economic factors. These factors evolve at lower frequencies and are absorbed by the rich set of fixed effects.", page 41

Moreover, I have added a regression using an interaction between weekends or holidays and temperature to deal with your comment (see Table A3.35). I discuss this in the thesis:
"To address potential heterogeneity between weekdays and non-working days, the baseline specification is extended by interacting temperature with an indicator for weekends and public holidays (Table A3.35). The results reveal a statistically significant positive interaction between temperature and non-working days, indicating that the effect of temperature on crime is stronger on weekends and holidays.", page 52

Regarding your comment on the effect of police deployment, see my reply below.

- Reported crime comes from police records and is therefore jointly determined by true underlying criminal behavior, victim reporting behavior, and police capacity. Weather plausibly shifts the later two factors. For instance, high temperature may increase willingness to report or the likelihood that police can identify perpetrators. This identification risk is acknowledged late in the chapter but not integrated into the causal interpretation. temperature. It is not easy to solve the endogeneity problem, but the authors should spend some paragraph to discuss the potential pitfalls.

> ***Author reply:***
>
> *I am unable to test victims' likelihood of reporting crimes; however, my data enable me to test whether the police are more effective in crime investigation at high temperatures. The results of this regression are provided in Table A3.37. Moreover, I have added a paragraph to the thesis to explain this in more detail:*
> *"Finally, I test whether weather affects police effectiveness rather than underlying criminal behavior using a case-study regression framework in which the dependent variable indicates whether an individual crime was cleared. If higher temperatures increased police activity or effectiveness, this would imply higher clearance rates and raise reverse causality concerns. The results do not support this channel. Estimated temperature effects are generally small, and even where statistically significant, most notably for assaults and thefts, the magnitudes are economically negligible. Moreover, the estimated temperature coefficient is negative, which runs counter to the reverse causality interpretation. Overall, weather-induced changes in police effectiveness are unlikely to drive the main findings (Table A3.37).", page 52*
> *However, analysis of weather effects on police productivity remains an open question for further research.*

Essay 3

- Match conditions are implicitly treated as quasi-random realizations of temperature. Whereas, elite football scheduling may be endogenous. For instance, leagues adjust kickoff times (e.g. evening vs. afternoon) to manage heat, broadcasters favor specific matching pairs in prime slots, and strong vs. weak team pairings are not randomly assigned across temperature bins. This creates a channel where temperature is correlated with opponent quality, fatigue, or tactical style. The paper should have explicitly addressed the endogeneity of scheduling rather than assuming temperature is conditionally random after fixed effects.

Author reply:

I have provided a robustness check using an interaction between match attendance and temperature (Table A4.22) to assess whether the temperature effect on soccer productivity is particularly pronounced during highly attended matches. I have added a paragraph to the thesis to explain this in more detail:
"To examine whether high-profile matches are systematically scheduled in response to television requirements and therefore correlated with temperature, stadium occupancy, used as a proxy for match salience, is included together with its interaction with temperature. The results in Table A4.22 indicate that the estimated temperature effects are not driven by selectively scheduled top matches.", page 117

- The author could have demeaned the temperatures before cutting into bins. The regression result with demeaned and binned temperature could have served as a easy-selling robustness check, as the same binning rule for all countries may seem counterintuitive. Specifically, leagues based in warmer locations (e.g. Brazil) nearly never hold games in the lowest bin. and leagues based in colder locations (e.g. Sweden) barely hold games in the highest bin. Another convincing design would use deviation from that club's typical local temperature or weather forecast for that time of year. That would better isolate unusual conditions rather than climate variations.

Author reply:

I have extended the thesis by analyzing demeaned temperatures, which are constructed by subtracting league-specific mean temperatures and subsequently discretized into 9 and 11 bins (see Table A4.23 and Table A4.24). I discuss this extension in the following paragraph of the thesis:
"As an alternative to the baseline specification, temperature is demeaned by league-specific means and discretized into 9 and 11 bins. The results remain qualitatively unchanged, with stable effect sizes and significance patterns, Table A4.23 and Table A4.24. The same conclusion holds when using home_away team fixed effects (see Table A4.25, Table A4.26, and Table A4.27).", page 117

Overall evaluation:

Across the three essays, the strength of the causal claim is not uniform, but the tone often is. The meta-analysis essay primarily characterizes the published literature and publication bias, The Czech crime chapter is closer to a short-run causal design using within-district daily shocks, and the football chapter is observational with nontrivial selection in scheduling. The thesis currently presents these as if they all deliver comparable causal evidence on the impact of temperature, which potentially overstates what the research agenda can identify. The three papers have inconsistent structures. For instance, the abstract for the first essay is missing, and the integrated abstract for all three papers inverts the order of essay one and essay two. The paper also suffers from inconsistent references. Moreover, the author references tables or sections that do not even exist. The reference systems are also inconsistent in the three essays. The formal statements of the lemmas referenced in the main content are missing. It remains unclear how the lemmas are used in the main content as well. - There are multiple over-sized tables and formulae in the content. It is suspected that some tables are incomplete in the paper (e.g. table 6 and 7 in the third essay). There are also obviously wrong labels for figures.

> ***Author reply:***
>
> *Thank you for this comment. I have checked the thesis, added the missing abstract for chapter 2 and proofread the thesis using Grammarly.*

A.2 Alexander Ahammer Ph.D.

This is a cumulative thesis that consists of three distinct papers. A common theme running through the chapters is the role of weather and how it affects human behavior, in particular in the domains of crime and productivity. In this report, I first briefly summarize each chapter in turn. I then provide my overall assessment of the thesis and discuss potential avenues for improvement. The first essay investigates whether higher temperatures causally increase homicide rates by conducting a meta-analysis of 156 estimates from 20 empirical studies covering multiple countries and time periods. The author harmonizes effect sizes to a common “per 1°C” impact on homicides per 100,000 inhabitants, carefully reconstructs coefficients from different re- porting formats, and documents substantial variation in study design, data frequency, and estimation methods. Using funnel plots, a battery of linear and nonlinear tests for publication bias, and meta-regressions with Bayesian model averaging, the essay shows that the positive temperature–homicide association reported in the literature is largely driven by selective re- porting. Once publication bias and study characteristics are accounted for, the mean effect be- comes statistically insignificant, while heterogeneity analysis reveals that studies using monthly data tend to report larger effects, whereas studies using Asian samples or OLS estimation tend to report smaller or even negligible effects.The second chapter examines the short-run effects of weather on crime and the mechanisms through which these effects operate, using a daily district-level panel for the Czech Republic from 1996 to 2016. The author links police records on homicides, assaults, sexual crimes, thefts, and robberies to meteorological data on temperature, precipitation, visibility, and air pressure, and estimates fixed effects regressions where identification comes from within-district day-to-day variation in weather. The results show a positive linear relationship between temperature and most crime categories, except homicide, and an inverted U-shaped relation- ship for assaults, thefts, and robberies. By exploiting information on offender characteristics, the chapter argues that alcohol consumption mediates the temperature effect for sexual crimes, thefts and robberies, and that temperature effects on assaults and thefts are stronger for male offenders, while age does not appear to systematically moderate the weather/crime relationship. Precipitation reduces assaults and sexual crimes, and higher visibility raises assaults and thefts, which the author interprets as supporting routine-activity style mechanisms whereby “good” weather increases the likelihood that offenders and victims meet. The third chapter studies how temperature affects human productivity using professional soccer as a high-frequency, team-based work setting. Using match-level data from ten countries across three continents between 2006 and 2024, the author links detailed performance statistics (grouped into attacks, defense and possession, and aggression) to stadium-level weather conditions at kick-off, and estimates fixed-effects models identified from within-stadium-year variation, with controls for home and away team by year and referee by season. The analysis shows that warmer conditions generally increase attacking efficiency–raising goal productivity and set-piece conversion–while weakening defensive performance and lowering passing accuracy, and that player aggression follows an inverted U-shaped relationship with temperature. The chapter also documents substantial heterogeneity: temperature effects are stronger in lower domestic leagues, the Champions League appears least sensitive to heat, and teams originating from colder regions, particularly in Brazil, experience larger declines in passing volume when playing in high temperatures.

Contribution

I recognize several original contributions in this thesis. In Chapter 1, the author conducts a very valuable exercise by essentially collapsing a large and policy-relevant literature on temperature and homicide into a single point estimate and asks how much of the apparent effect survives once they account for publication bias; to my knowledge, this is the first meta-study focused specifically on this question. In Chapter 2, the thesis contributes by providing evidence on weather and crime outside the United States and developing countries, and by documenting effects for a broader set of weather measures beyond temperature alone. In Chapter 3, the author contributes new evidence on productivity effects of weather fluctuations in a professional soccer context, using data from multiple continents. Taken together, these chapters represent valuable and original contributions by the author, and I expect the findings to be published in reputable economics journals.

Is the thesis based on relevant references?

Yes. In each chapter, the author situates the work clearly within the relevant literature and engages carefully with the key contributions in economics and related fields. The literature overviews are comprehensive, up to date, and well structured, and they convincingly highlight the gaps that the thesis seeks to fill.

Is the thesis defendable at your home institution?

Yes. Based on the quality of the contribution, the empirical execution, and the overall coherence of the thesis, I consider it clearly defendable at my home institution. In fact, I would place it in roughly the top 5% of recent PhD theses by graduating students.

Do the results of the thesis allow their publication in a respected economic journal?

Yes. In my view, each chapter has realistic publication prospects in respected economics journals. Chapter 1, as a well-executed meta-analysis on a policy-relevant topic, has a good chance in general interest outlets that regularly publish survey and meta-analytic work, such as the Journal of Economic Surveys. Chapter 2, with its careful daily crime/weather analysis outside the usual US/developing-country settings, could plausibly place in a strong applied micro or labor/crime outlet, such as the Journal of Human Resources. Chapter 3 speaks to both labor and sports economists, and journals such as Labour Economics, the Journal of Economic Behavior & Organization, or more specialized outlets like the Journal of Sports Economics seem like realistic publication targets.

Are there any additional major comments on what should be improved?

I do have some additional comments, most of which concern presentation and framing rather than the core empirical work. Overall, I would have hoped for somewhat more guidance on the potential psychological and especially biological mechanisms governing the relationship between different weather measures and crime/productivity. This could already be developed in the general introduction, and would help motivate why, for example, temperature, precipitation, and air pressure might generate different behavioral responses, an issue that is particularly salient in Chapter 2. In addition, I recommend a careful read-through and possibly professional language editing: there are still some typos and occasionally awkward or imprecise formulations.

> ***Author reply:***
>
> *I have extended the introduction of the thesis to include literature discussing biological mechanisms linking temperature and productivity.*
> *"A growing body of interdisciplinary research suggests that weather conditions may influence human behavior through biological and psychological mechanisms. For example, ambient temperature has been linked to modulation of serotonergic neurotransmission and physiological discomfort that can increase impulsivity and aggression (Garza-Trevino (1994); Nelson & Chiavegatto (2001); Nelson (2005)), while temperature and precipitation also impact cognitive function, mood, and stress responses, which in turn shape social interactions and productivity outcomes (Nelson & Trainor (2007); Mazlan* et al. *(2020)).", page 1*
>
> *Moreover, I have checked the thesis, added the missing abstract for chapter 2 and proofread the thesis using Grammarly.*

For Chapter 1, when discussing publication bias, I would have liked to see a simple plot of the distribution of t-values across estimates, to visually assess whether there is missing mass around conventional significance thresholds.

> ***Author reply:***
>
> *I added a plot of t-values across estimates (see Figure A2.4) and a caliper test for p-hacking (Gerber & Malhotra (2008)). I discuss these and potential p-hacking issues in the estimates in the following paragraph:*
> *"The distribution of t-statistics in the Figure A2.4 across estimates is presented to visually assess potential discontinuities around conventional significance thresholds. Neither visual inspection nor the formal caliper test following Gerber & Malhotra (2008) indicates suspicious clustering around the 1%, 5%, or 10% levels, suggesting no evidence of p-hacking.", page 17*

For Chapter 2, I would soften the language around alcohol consumption as a mechanism. As written, the chapter sometimes suggests that weather affects crime through alcohol, but the empirical design only shows that weather is correlated with both alcohol-related variables and crime; even if alcohol and crime were orthogonal, the reported patterns could look similar. It may also be possible to streamline the presentation by reducing the number of tables, and by slightly expanding the text at key points so that it is always crystal clear what is being estimated. Finally, you mention the use of Poisson models, but what you label as Lemma 3.2 (and, I believe, also 3.1) relies on linear model properties and does not directly apply in the nonlinear Poisson case.

> ***Author reply:***
>
> *I have rewritten Chapter 3 so that I now consider alcohol as a mechanism linking weather and crime, while treating the sex and age of the offenders more as sources of heterogeneity in the effects. Moreover, I agree that the Lemmas cannot be directly applied to Poisson regression; therefore, I did not include them in the appendix. Instead, I made the section describing the comparison of regression coefficients among subgroups clearer and more intuitive:*
> *"I test the statistical effect of temperature on crime rates between categories (i.e. all crimes together vs alcohol, gender and age groups) using the following three methods:*
> *Firstly, I assume that the ratio between all crimes committed, irrespective of their clearance rate, and each subcategory of crimes remains constant*

over time (i.e., the number of crimes committed under the influence of alcohol, committed by women, and across different age groups). If the average value of the dependent variable (i.e., the daily crime rate) for all crimes equals the average value of the daily crime rate in a subcategory multiplied by a coefficient k, then the resulting beta estimate for the effect of weather on crime for each individual specification can also be multiplied by this coefficient k.
The second method assumes that the sum of the weather effect estimates for all subgroups of offenses equals the estimate obtained from a regression run on all offenses committed, irrespective of clearance rate. In other words, the beta estimate for crimes committed by men plus the beta estimate for crimes committed by women equals the beta estimate from the regression on all crimes. This approach is similarly applied to other subcategories, such as alcohol consumption and offender age. Given that a 100% clearance rate is unrealistic in real life, I multiply the number of offenses in each subcategory by the inverse of the clearance rate.", page 42

For Chapter 3, I encourage you to carve out the contribution a little more, explaining why professional soccer is a particularly interesting setting for studying weather and productivity (e.g., teamwork, high stakes, abundant performance metrics). In Section 4.5, the equations are not strictly necessary; the core issue is not so much within-team cooperation as the fact that you observe equilibrium outcomes between two teams playing against each other, so one team's gain is the other's loss. This is difficult to resolve empirically, but it deserves a bit more conceptual discussion. Finally, the chapter currently includes a very large number of figures and tables, and some consolidation would improve readability.

Author reply:

I have extended the introduction of Chapter 4 by providing more motivation for why soccer is a suitable setting for studying weather and productivity:
"Professional soccer represents a particularly compelling and relevant setting to study the effects of weather on human productivity because it combines well-measured, high-stakes team output with complex coordination under environmental stressors. Recent empirical evidence shows that ambient temperature systematically influences both physical and technical performance metrics in elite soccer, such as running distances, sprint

> *efforts, and team engagement, making it a valuable analog for productivity in other collaborative, high-performance contexts (Illmer & Daumann 2022; Link & Weber 2017; Wei* et al. *2023)", page 92*
>
> *Moreover, I moved the equation from Section 4.5 into the appendix and clarified the within-team interaction mechanisms in more detail. I also merged relevant tables and figures (see Figure A4.2 - Figure A4.9) to consolidate the appendices.*

Overall assessment of the thesis

Overall, I assess this as a very strong thesis. The three chapters offer clear and original contributions on weather, crime, and productivity, are empirically well executed, and in my view have realistic publication prospects in reputable economics journals. The work is carefully done, the data and methods are appropriate, and the main conclusions are well supported by the evidence. My suggestions above concern mostly framing, language, and some refinements in interpretation and presentation, and do not detract from my positive overall evaluation. I therefore recommend the thesis for defense without substantial changes

A.3 Mariola Pytliková Ph.D.

Vojtěch Mišák's dissertation Essays on Weather, Crime and Productivity consists of Introduction and three self-contained empirical chapters exploring how weather affects human behavior, especially crime and productivity. Chapter 2 – Does Heat Cause Homicides? A Meta-Analysis The author compiles 156 estimates from 20 studies of the temperature–homicide relationship. He detects strong publication bias and shows that the widely claimed positive effect of heat on homicides becomes statistically insignificant once corrected (e.g., corrected mean effect in the conclusion is zero). The essay also identifies heterogeneity: studies using monthly data report larger effects, while those from Asia or using OLS tend to find smaller ones. Chapter 3 – Exploring the Mechanisms Between Weather and Crime: Insights from the Czech Republic Using daily district-level data (1996–2016), the author estimates the effects of temperature, precipitation, visibility, and air pressure on five crime categories (homicide, assault, sexual crime, theft, robbery). He finds:

- Temperature increases crime, except homicides.

- Assaults, thefts, and robberies follow an inverted U-shaped relationship with temperature.
- Alcohol consumption mediates effects on sexual crimes, thefts, robberies.
- Effects are stronger for male offenders; age is not a major factor.
- Precipitation reduces crime. Chapter 4 – Temperature and Productivity in Soccer Using match-level data from ten countries across three continents, the author analyzes temperature effects on player performance. He finds:
- Warmer weather increases attacking efficiency (higher goal productivity, shot conversion).
- It reduces defensive actions and passing accuracy.
- Fouls show an inverted U-shape with temperature.
- Effects are stronger in lower leagues and among teams from colder climates, which adapt poorly to heat.The overall conclusion emphasizes that weather affects behavior, but in heterogeneous and context-dependent ways, and challenges some widely held assumptions (e.g., that heat universally increases violent crime) while highlighting new mechanisms (e.g., alcohol mediation in crime; non-linear performance effects in soccer).

Address the following questions in your report, please:

a) Can you recognize an original contribution of the author?

The dissertation thesis contains Introduction and three empirical essays which, taken together, provide an original and coherent contribution to the literature on weather, crime and productivity.

- The first essay provides a meta-analysis of 156 estimates from 20 studies on the effect of temperature on homicide. The author systematically documents publication bias and uses linear, nonlinear methods and Bayesian model averaging to correct for it. After this correction, the mean effect of temperature on homicide becomes statistically insignificant, and the paper also identifies sources of heterogeneity such as data frequency and regional coverage.

- The second essay uses rich daily district-level crime data for the Czech Republic over 1996–2016 to study how temperature, precipitation, visibility and air pressure affect five crime categories and their heterogeneity by alcohol use, gender and age of the offender. The careful exploitation of high-frequency data from a Central European setting and the detailed focus on mechanisms (especially alcohol) are, to my knowledge, new in this context.

- The third essay employs a large match-level panel from professional soccer in ten countries (plus the Champions League) to study the nonlinear effect of temperature on attacking, defensive and aggression-related performance indicators. It shows that warmer conditions increase attacking efficiency but reduce defensive control and that teams from colder climates are less adapted to high temperatures.

The combination of meta-analysis, administrative crime data, and sport productivity data is itself original and gives a broad, multi-angle view on how weather and climate shape human behavior and performance. To conclude, I find the thesis to make an original contribution in the area of environmental economics, crime economics, and behavioral economis.

b) Is the thesis based on relevant references?

The dissertation draws on extensive and appropriate literature. Across chapters, the author refers to major strands of the literature on weather, crime, climate–violence links, meta- analysis / publication bias, and temperature effects on productivity and sports performance. The related-literature sections are generally up to date and well structured.

c) Is the thesis defendable at your home institution or another respected institution where you gave lectures?

The dissertation meets the expected standards for PhD theses at CERGE-EI and other respected European institutions, such as Aarhus University, where I also worked for a longer time. The empirical work is serious, with large data sets, clear identification strategies and appropriate econometric methods. The main findings are plausible and consistent with related research. The thesis is also overall well written and logically structured. While some parts of the text and tables need polishing, the scientific level meets the standards for a PhD in economics. Thus yes, in my view, the dissertation would be defensible at CERGE-EI.

d) Do the results of the thesis allow their publication in a respected economic journal?

The essays stand on their own as publishable papers and have all realistic publication potential. Overall, I see realistic prospects for publishing at least two of the three essays in respected outlets.

e) Are there any additional major comments on what should be improved?

My main comments concern clarification of mechanisms, some data and table issues, and additional robustness / sensitivity analyses. These comments are intended to strengthen the pre-defense and subsequent publication prospects:
1. General

- The overall structure of the thesis is clear and logical: an introduction followed by three self-contained research papers.
- The empirical work is generally careful and transparent.
- Language and typos: Before the final defense, I recommend a thorough proof-reading to correct minor typos, spacing issues, and small inconsistencies in references and tables, as well as fix formatting issues (e.g. "Therefor" → "Therefore" on page 86, occasional missing spaces, and consistent use of parentheses for citations, table formatting -chapter 4 especially.. etc.).
- Be consistent in terminology: use "weather" vs "temperature" vs "climate" consistently and explain early how you use these terms in the thesis (weather = short- term conditions, climate = long-run averages, etc.). Perhaps consider term: weather variability or temperature variability.

  Author reply:

  I have checked the thesis, added the missing abstract for chapter 2 and proofread the thesis using Grammarly.

2. Chapter 3: Clarify the "mechanisms". The title promises "mechanisms between weather and crime", but in practice the main explored mechanism is

alcohol; gender and age are more like heterogeneity dimensions.. It would help to state clearly in the introduction which mechanisms are analyzed: for example, (i) adaptation / physiological discomfort (negative affect and aggression, captured by the General Affect (GA) and Negative Affect Escape (NAE) models), (ii) routine-activity channels (how weather changes outdoor activities and opportunities for crime), and (iii) alcohol use as a mediating channel. A short paragraph that strenghten explaination of the adaptation and routine-activity channels with references to the key theoretical literature would be useful. Gender and age differences could be described more clearly as heterogeneity in treatment effects rather than separate mechanisms. Below, I suggest a few concrete robustness checks that are directly tied to mechanisms.

> ***Author reply:***
>
> *I have rewritten Chapter 3 so that I now consider alcohol as a mechanism linking weather and crime, while treating the sex and age of the offenders more as sources of heterogeneity in the effects.*

3. Chapter 3: Suggestions for empirical extensions and robustness checks a. Temperature extremes and non-linearities. The chapter already considers non-linear GA vs NAE relationships and some “extreme temperature” indicators. To sharpen the adaptation / negative-affect mechanism, one could: i. Experiment with more bins (e.g. 5°C or decile bins), and use indicators for very hot days (>25°C or >30°C) and perhaps very cold days. ii. Use degree-day style measures (e.g. number of days above a high threshold in a week or month), iii. Compare the impact of a single very hot day with the impact of several hot days in a row.iv. Measures of temperature variability or anomalies (e.g., deviation from district-specific seasonal average). This would help to connect more directly to adaptation and to the idea that “unusual” weather may matter beyond the level. Also it might uncover that it is not only the level of temperature but also the accumulation of heat stress that matters for aggression and crime.

> ***Author reply:***
>
> *I have conducted several robustness checks you mentioned earlier. The results are provided in Table A3.35 and Table A3.36, with my comments in a new paragraph:*
> *"In addition, cumulative heat exposure and temperature anomalies, such as consecutive hot days and weekly temperature maxima, are examined*

to assess whether aggressive behavior intensifies beyond the temperature level itself, Table A3.35 and Table A3.36. The results indicate that these alternative specifications do not alter the overall interpretation of the baseline findings, remaining consistent with both adaptation-based responses and the General Aggression and Negative Affect Escape frameworks discussed above.", page 52

b. Routine-activity and work/absence channels. Temperature effects on crime might be mediated by work and absence from work which would fit very well with routine-activity theory. Even without detailed individual labour data, some simple interaction checks seem feasible: i. Interact temperature with an indicator for working day vs weekend, and if possible with public holidays, to test whether temperature has stronger effects when more people follow regular work routines. ii. Interact temperature with an indicator for school holidays, which could capture changes in youth and family routines and in time spent outdoors. iii. If data on unemployment or/and vacancy rates, one could also explore whether weather–crime effects are stronger in areas with higher unemployment rates. Even if these analyses remain exploratory, they would provide more direct evidence on the routine-activity and work- related channel that is now mostly discussed qualitatively.

Author reply:

I have added regressions on both temperature interactions with weekends and with public holidays (Table A3.35). I discuss the results in a new paragraph of the thesis:
"The interaction results with non-working days, defined as weekends and public holidays, indicate that temperature effects on crime are generally stronger when regular work routines are suspended, Table A3.35. Specifically, positive and statistically significant interaction terms are observed for assaults, sex crimes, thefts, and robberies, whereas no corresponding interaction effect is found for homicides, consistent with a routine-activity mechanism driven by increased social interaction and exposure.", page 55

Unfortunately, I do not have data on unemployment or vacancy rates at the district level. However, since I use daily data and my identification strategy relies on daily variation between temperature and crime, I do not expect long-term unemployment data to affect my overall results. I commented on this in the following sentence of the thesis:

> *"The identifying variation comes from within-district, day-to-day fluctuations in weather, which are plausibly exogenous to short-run changes in economic activity and other socio-economic factors. These factors evolve at lower frequencies and are absorbed by the rich set of fixed effects.", page 41*

c. Clarifying mechanisms vs heterogeneity in the discussion. In Section 3.6 and the conclusion, it would help to be very explicit about what is interpreted as a mechanism and what is heterogeneity. For example, the GA/NAE vs RA comparison and the alcohol channel are clearly mechanism- level interpretations, while differences by gender and age are better described as differential exposure to those mechanisms (through outdoor work, time spent outside, and drinking patterns). Making this distinction explicit would make the "mechanisms" contribution of the chapter more focused and credible.

> ***Author reply:***
>
> *I have rewritten Chapter 3 so that I now consider alcohol as a mechanism linking weather and crime, while treating the sex and age of the offenders more as sources of heterogeneity in the effects.*

d. Identification details. Your fixed-effects specification is appropriate. To reassure readers, you might briefly discuss possible remaining confounders (e.g. time-varying district-level shocks that correlate with weather) and why they are unlikely to bias short-run weather effects.

> ***Author reply:***
>
> *I have elaborated on this comment in a following sentence:*
> *"The identifying variation comes from within-district, day-to-day fluctuations in weather, which are plausibly exogenous to short-run changes in economic activity and other socio-economic factors. These factors evolve at lower frequencies and are absorbed by the rich set of fixed effects.", page 41*

4. Chapter 3 - MINOR: Data and table issues a. Table 2 (page 34): As noted above, clarify why the maximum number of homicides in the "All" category is lower than what one would get by summing male/female or alcohol/non-alcohol maxima. A short note explaining that these categories are not additive at the district-day level (or correcting the table if needed) will avoid confusion. b. Add a clear data source statement for the daily crime data in Sections 3.3 and 3.3.1

Author reply:

I adjusted the Note below Table 3.2 to make it more self-explanatory.

I added a footnote explaining the data source into the relevant section: "Crime data come from the crime statistics system of the Police Presidium of the Czech Republic ("Evidenčně statistický systém kriminality Policejního prezidia ČR")", page 38

5. Chapter 5: MINOR: a. Clarify the variable "Climate" - consider renaming the variable to something like "Colder climate"; This will make table interpretation more transparent. b. Fix the layout of Tables 6 and 7 so they match the horizontal page (possibly using landscape). At present the frames and orientation seem off..6. Chapter 4 – MINOR: Additional robustness and nonlinearity As in the crime chapter, consider testing alternative definitions of heat and nonlinearity, e.g. Narrower or wider temperature bins; or use alternative cut-offs for "hot" matches; This would show that your main patterns are not driven by an arbitrary binning choice.

Author reply:

I have renamed "Climate" variable to "Colder climate" to make tables more self explanatory.

Moreover, I have extended the thesis by analyzing demeaned temperature (also recommended by another opponent), which is constructed by subtracting league-specific mean temperatures and subsequently discretized into 9 and 11 bins (see Table A4.23 and Table A4.24). I discuss this extension in the following paragraph of the thesis:
"As an alternative to the baseline specification, temperature is demeaned by league-specific means and discretized into 9 and 11 bins. The results remain qualitatively unchanged, with stable effect sizes and significance patterns, Table A4.23 and Table A4.24.", page 117

7. Chapter 4: Link to mechanisms: You already cite literature showing that heat affects physical performance and decision-making of players and referees. It might be useful to link this more explicitly to your own results: e.g., heat reduces defensive intensity and passing accuracy, which may be consistent with fatigue and concentration loss, while attacking efficiency may increase because defenses exhaust faster.

Author reply:

I have added the following sentence to the relevant section to address this comment:
"These results are consistent with heat-related fatigue and loss of concentration, which can reduce defensive effort and passing accuracy, while attacking efficiency increases as defenses tire more quickly.", page 118

8. Chapter 2: Tighten the interpretation of publication-bias results. The plots and tests show the presence of publication bias and the overall effect becomes insignificant when corrected. It would help to emphasize that this does not mean there is NO relationship anywhere, but that the average effect is smaller and more uncertain than suggested by the raw literature. You can connect this back to the policy debate on climate and violence. 9. Chapter 2 - Minor: Highlight the contribution relative to existing meta-studies. You may briefly mention how your scope (focus on homicide, choice of methods) differs from previous meta-studies on climate and interpersonal violence, to make the novelty transparent.

Author reply:

I added a footnote to clarify the interpretation of publication bias:
"This does not imply that temperature is unrelated to violence in all contexts, but rather that the existing evidence does not support a strong or systematic effect on homicide rates, which is relevant for policy debates linking climate change to violent crime.", page 24

I added the following sentence to the introduction of Chapter 2:
"Unlike existing reviews and meta-analyses on weather, climate, and violence (Corcoran & Zahnow (2022); Choi et al. *(2024)), which cover a broad set of crime categories or provide mainly narrative syntheses, this paper focuses exclusively on homicide rates as the most comparable outcome across countries. Moreover, I apply recent meta-analytic techniques commonly used in economics, including extensive publication-bias corrections and methods that account for study heterogeneity, which have not been systematically employed in prior meta-studies on climate and interpersonal violence.", page 5*

f) What is your overall assessment of the thesis? (a) I recommend the thesis for defense without substantial changes, (b) the thesis can be defended after revision indicated in my comments, (c) not-defendable in this form.

Based on the evaluation criteria, my conclusion is: (a) I recommend the thesis for defense without substantial changes.

This is a strong and promising dissertation The empirical work is solid, the datasets are rich, and the three essays make clear and original contributions to the literature on weather, crime, and productivity. The requested revisions are not structural; they are mainly oriented toward strengthening the presentation of mechanisms, clarifying some data details, and expanding a few robustness checks to improve clarity and interpretability. None of these issues affect the core validity or defensibility of the results. In my view, the thesis fully meets the standards for a PhD dissertation, and the suggested improvements can be addressed during the final revision stage (some, which the author consider useful may be addressed before the regular defense and/or submissions to journals).