Crime and weather. Evidence from the Czech Republic.

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Abstract

This article estimates the impact of weather on crime in the Czech Republic. Using detailed crime data during the years 2005-2015, I show that temperature has a significant positive effect on the total number of assaults, thefts, robberies and sexual crimes recorded. Furthermore, precipitation is found to have a negative significant effect on the number of assaults and sexual crimes committed. Finally, based on my results, temperature seems to cause an overall increase in assaults‘ and thefts‘ rates. Heat effect on sexual crimes is more a substitution effect between cold and hot days.

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Introduction

"In the summer months, the bad guys tend to be deadliest."[1]

Climate change is a frequently discussed issue not only in academic debates. The effect of weather on criminal activity is examined by psychologists (for example Anderson *et al.* (2000)) or by criminologists and economists (for example Coccia (2017)). Criminology research has focused primarily on the short-term relationship[2] between crime and weather to show that higher temperatures cause substantial increases in crime (Ranson (2014)).

The important question of climate change gives rise to many issues. According to Miles-Novelo & Anderson (2019), psychological, sociological, political and economic consequences of rapid climate change will cause an increase in violent behavior such as violent crime, terrorism and even international wars. Moreover, Burrows & Kinney (2016) argue that climate change increases migration rates. Higher migration leads to higher risk of conflict.

I aim to fill the following gaps in the literature. The majority of research on the topic has been conducted on US data; little is known about crime and weather in Central Europe (most notably recent study by Otrachshenko *et al.* (2021)). To the best of my knowledge, this article is the first study on Czech data in this field. Moreover, majority of literature investigates property and violent crimes together. I focus on separate crime categories which makes me able to analyze weather impacts on crime more in detail.

I focus on five types of criminal activity - homicides, sexual violence, thefts, assaults and robberies. In particular, I estimate the short-run causal link between temperature and rain on crime. Crime data are aggregated to the district and daily level and matched with the weather statistics from the Czech Hy-

[1] New York Times, June 19, 2009. Available here:
https://www.nytimes.com/2009/06/19/nyregion/19murder.html

[2] The long-term link between crime and weather is also a subject of academic research, especially the relationship between climate change and future changes in the crime rate. See Ranson (2014).

drometeorological Institute.

I find evidence that temperature has a significant positive effect both on sexual crimes, thefts, assaults and robberies. Moreover, rain significantly decreases total number of assaults and sexual crimes.

Moreover, I have constructed a test to check if presented weather effects on crime might have implications for the climate change. Based on my results I argue that the effect of temperature on sexual crimes is more substitution effect from cold to hot days. On the other hand, temperature causes a real increase in assaults‘ and thefts‘ rates.

Literature review

Numerous studies investigate the link between weather and peoples’ decisions.

One such hypothesis draws on social interaction theory. That is, weather is one of the aspects that fosters social interactions between people, and through that, it is likely to increase criminal activities, Glaeser *et al.* (1996). This hypothesis holds both for the behavior of victims and offenders. For example, when it rains, people stay home rather than meet with other people in the park. This lowers the probability of pickpocketing and similar crimes. However, thieves also adapt their strategies, e.g. it is easier to rob a country cottage on a cold, rainy day because its owners prefer to remain in the city on that day. This behavior is theoretically described by the sociological theory of opportunities, Cornish & Clarke (2014).

Another explanations is built on experimental evidence that temperatures affect human aggression (most notably Card & Dahl (2011) or Anderson (1989)). These experiments imply that violent crimes might be caused by unpleasant weather conditions. In their paper Chersich *et al.* (2019) investigate connections between hot weather and violence in South Africa. The authors identify "transmission channels" through which high temperature affects criminality. They argue that *"Heat exposure has a range of physiological sequel, affecting levels of comfort, emotional stability and sense of wellbeing. Being in an un-*

comfortably hot environment foments irritability and aggressive thoughts, and reduces positive emotions such as joy and happiness." According to the authors, men are especially sensitive to the effects of high temperature on aggression.

Another aspect that has to be taken into account is the connection between alcohol use, aggression and heat. Chersich *et al.* (2019) argue that alcohol causes dehydration, which is associated with mood disturbance and anger itself.

Although empirical studies have not distinguished between these channels, there is enough evidence that weather affects crime.

Horrocks & Menclova (2011) investigate New Zealand's police daily data from 2000 to 2009. They find that high temperature and precipitation both have a significant positive effect on the number of violent crimes. Moreover, temperature also has a significant positive effect on the number of recorded property crimes.

Ranson (2014) analyses 30 year panel US districts data of monthly crime and weather[1].

Ranson (2014) finds strong evidence that precipitation causes vehicle thefts. Furthermore, the probability of rape, assault and robbery is strongly affected by high temperatures.

Blakeslee & Fishman (2014) provide the first analysis of the causation between weather and crime from least developed country. Using detailed crime and weather data from Indian districts from 1971 to 2000, the authors investigate how weather shocks (high temperature and low rainfall) that reduce agriculture production affect criminality. There have not been many studies about the link between rain and sexual violence. Sekhri & Storeygard (2014) find an effect of a negative and positive rain shock on sexual crime against women in rural India. However, the causal relationship in this study is explained by shocks to agriculture production. Obviously, this conclusion cannot

[1] As opposed to Horrocks & Menclova (2011), author of this article decided to use a fixed-effects Poisson regression model to estimate the parameters for the following reasons:

Firstly, some types of crime (murder or manslaughter) are committed rarely, and thus the dependent variable takes zero for most observations. Log-linear OLS approach would therefor cause problems. Horrocks & Menclova (2011) solve this problem by dividing crime into only two types - property crime and violent crime. However, Ranson (2014) seeks to investigate different types of crime more in detail, and thus his decision of choosing the Poisson model accommodates these zero values.

Secondly, maximum likelihood estimates are unbiased even if crime data do not perfectly match Poisson distribution.

Thirdly, although Ranson (2014) uses a large number of multiplicative fixed-effects, his Poisson regression does not suffer from an incidental parameters problem. In other words, temperature and precipitation coefficients and fixed effects can be estimated jointly be applied to the situation in the Czech Republic. In other words, days without or with a significant amount of rain probably do not impact Czech agriculture output on the same day.

Methodologically, Blakeslee & Fishman (2014) provide a log-linear regression in which yearly data were regressed on dummy variables controlling for positive and negative shocks in precipitation and rain. The dummy variable equals one when the standard deviation of rain or temperature is more than one above or below the mean, and otherwise takes zero.

Because log-linear approach causes problems when the dependent variable equals zero, the authors replaced the logarithm of the dependent variable with zero, where the crime incidence is zero. In the dataset by Blakeslee & Fishman (2014) only 2% of the sample report zero crime rates. In contrast to Ranson (2014), Blakeslee & Fishman (2014) did not have to adopt a Poisson specification. Blakeslee & Fishman (2014) find that both property and non-property crimes are positively affected by extreme heat and rainfall.

Mares & Moffett (2016) study the effects of warmer temperatures on interpersonal violence on a sample of 57 countries. They also focus on the regional inequities of this issue. Mares & Moffett (2016) focus mainly on the long-term impact of high temperature and on climate change; they do not investigate the effects of one-day temperature peaks. Their results claim that a one degree Celsius increase in annual temperature is associated with a nearly 6% average rise in homicides. They found strong regional differences in the link between high annual temperature and crime rate. Almost no effect of temperature on crime is found in post-Soviet republics. Conversely, the strongest effect is found in Africa. Mares & Moffett (2016) argue that the regional variation in results is even more important because the majority of studies on this topic is from western countries, particularly from the USA.

Otrachshenko *et al.* (2021) study relationship between temperature extremes and violent crimes in Russia. They find that heat increases homicides, while cold temperature have no such effect.

Existing studies differ in the methodology they use. For example, Horrocks & Menclova (2011) and Baryshnikova *et al.* (2019) focus on the short-term relationship between crime and weather, while Ranson (2014) studies the effect of climate change on criminal activity. Moreover, existing studies differ in what data they use. Ranson (2014) analyses monthly crime and weather data, Gamble & Hess (2012) (2012) investigate daily fluctuations in temperate and crime activities, and Baryshnikova *et al.* (2019) use high-frequency hourly crime and weather statistics. These differences in the type of data are important because each data type is suitable for gauging a different relationship (short-term vs long term effect of weather on crime). Furthermore, although the majority of existing studies analyzed the linear relationship between crime and weather, some studies (for example **?**) analyzed a possible spatial-temporal trend in crime and weather data.

The effect sizes tend to be smaller in the studies in which identification is based on short-term fluctuation in temperature and rainfall (i.e. Horrocks & Menclova (2011)), compared to studies exploiting annual shocks or long-term changes in weather (i.e. Ranson (2014)).

The goal of this study is to provide empirical evidence on the following research questions:

- Does higher temperature or rain cause a higher crime rate in the Czech Republic?
- Does the effect differ among different types of criminal activity?
- Does these results have any implications for the climate change?

Data

3.1 Crime data

Daily crime data by district and characteristics[1] were reported from January 1, 2005 to December 31, 2015. Crime statistics at the incident level are aggregated to the analysis-ready level by computing daily sums of crime in a district per each crime category. We normalize the number of crimes by population (per 1 million).

Following Ranson (2014) or Gamble & Hess (2012), I aggregate criminal data into corresponding categories as described in Table 3.1.

[1] Characteristics describe each criminal activity, i.e. murder, theft, robbery, burglary, etc. Also known as TSK - *"Takticko-statistická klasifikace"* of crimes.

Table 3.1: Categories of crime data

Available Aggregated Data	**Corresponding Subcategories**
Homicide	Robbery murder, Sexual murder, Bounty murder, Murder motivated by personal relationships, Infanticide, Other murders
Theft	Larceny, Car theft, Simple theft
Sexual crimes	Rape, Sexual coercion, Sexual abuse
Assault	Manslaughter, Kidnapping, Injury, Taking hostages, Threatening, Extortion, Trespassing, Maltreatment
Robbery	Simple robbery, Bank robbery
Fraud	Fraud, Embezzlement

Figure 3.1: Number of crimes, monthly.

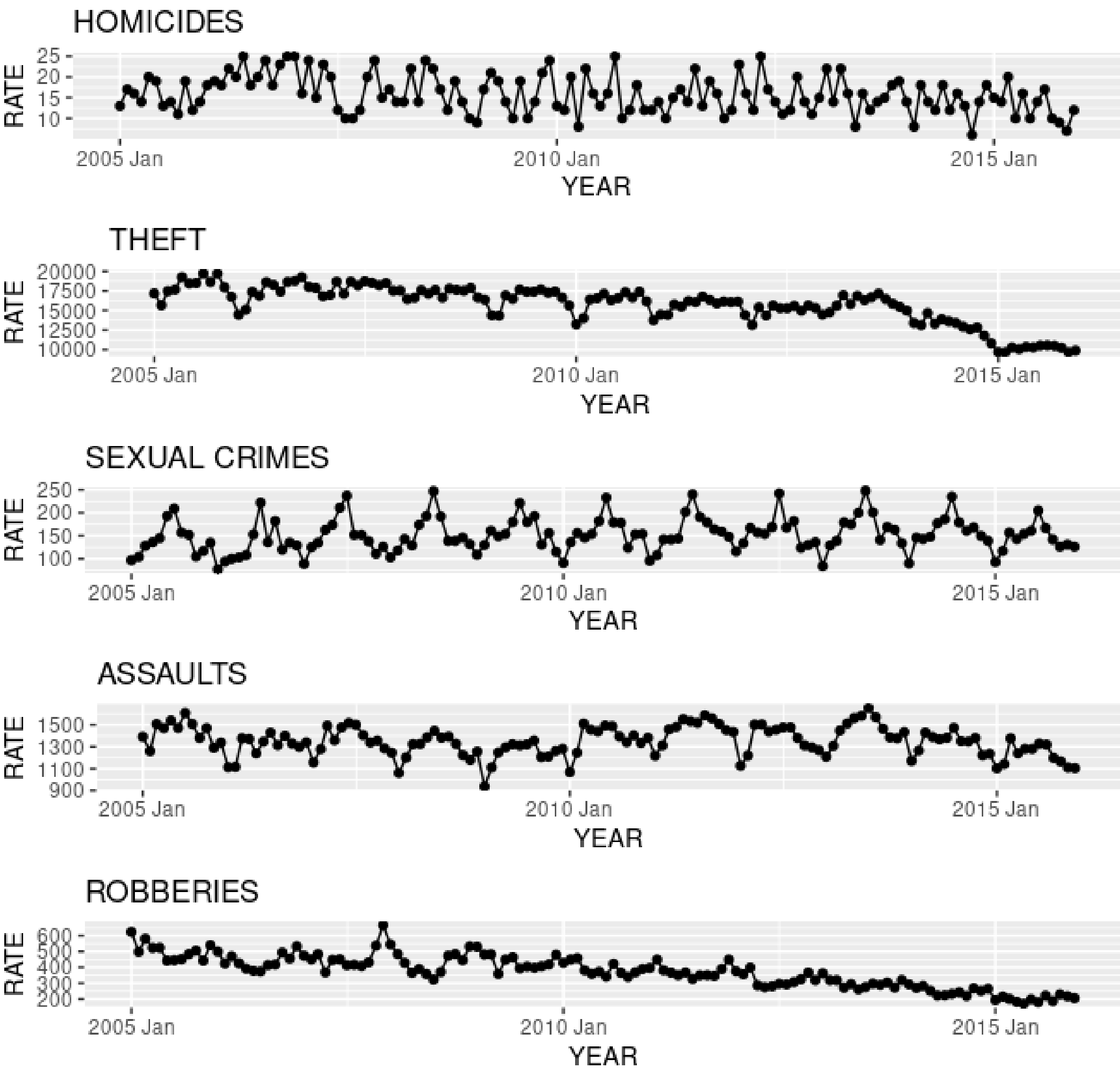


Figure 3.1 shows country-level aggregates of crime categories as described in Table 3.1. Firstly, there is a decreasing trend in the total number of crimes. Between 2014 and 2015, the strongest fall in crime frequency is observable for thefts, fraud and assaults. The number of robberies has been decreasing consistently since 2010. The decreasing trend in these crime categories is consistent with current literature, most notably Caneppele & Aebi (2019). Secondly, the number of homicides does not seem to have a falling trend over the years. Thirdly, I can observe a strong seasonal pattern in certain types of crime, namely sexual crimes and assaults.[2]

3.2 Weather data statistics

The Czech Hydrometeorological Institute collects daily weather data from 10 meteorological stations. It therefor is less detailed than crime data (80 districts). I assigned the weather data to the district based on the geographical distance of the nearest meteorological station[3]. I acknowledge that this is a limitation because I do not have full regional variation in my weather data[4]. This issue is further checked by a robustness check in Section 5.1.1.

I use the mean daily temperature as the main temperature variable in my regressions.[5] Moreover, the maximum daily temperature is used as one of the robustness checks in Section 5.1.1. Precipitation is measured as the total daily rain in mm.

Finally, I estimate the effect of temperature extremes on the crime levels. There are several ways to define what temperature level should one consider extreme in the Czech Republic. Firstly, I can follow Government Regulation No. 361/2007 Sb. determining conditions of occupational health protection. This Government Regulation defines long-term and short-term permissible work time in particular temperature conditions. Temperature lower than 0'C or higher than 26'C is considered as extreme temperatures for outdoor work. Secondly, another approach comes from climatological definitions of tropical day and ice day (Sobišek (1993)). Tropical day is defined as a day that has a higher maximal temperature than 30'C. Similarly, ice day (also known as Arctic day)

[2]More figures describing seasonal patterns in crime data are in Section A.1 in the Appendix.

[3]See Table A.2 in the appendix for details.

[4]See more in Section 4.2

[5]Note that mean daily temperature is used in the majority of existing studies.

is a day when the maximum daily temperature does not exceed –10'C. Thirdly, the Czech Hydrometeorological Institute publishes[6] criteria for issuing alert information. These weather alerts are announced when the daily temperature exceeds 31'C or the temperature falls bellow -12'C.

Given that outdoor activities are considered an important channel through which weather impacts crime, I follow the Government Regulation that defines permissible work time in high outdoor temperatures and use the 26'C maximum daily temperature as the heat threshold in my regressions.

Estimation

4.1 Econometric method

I follow standard estimation design in the literature to estimate the causal link between temperature and crime:

$$crime_{d,i} = \beta_0 + \beta_1 \cdot temp_{d,i} + \beta_2 \cdot C_{d,i} + \beta_3 \cdot \lambda\_d_{d,i} + \beta_4 \cdot \lambda\_ym_{d,i} + u_{d,i} \quad (1)$$

$$crime_{d,i} = \beta_0 + \beta_1 \cdot rain_{d,i} + \beta_2 \cdot C_{d,i} + \beta_3 \cdot \lambda\_d_{d,i} + \beta_4 \cdot \lambda\_ym_{d,i} + u_{d,i} \quad (2)$$

where β_0 is the intercept, $crime_{d,i}$ denotes the crime rate, $temp_{d,i}$ stands for average daily temperature, C is the set of control variables, $\lambda\_d_{d,i}$ and $\lambda\_ym_{d,i}$ is the set of district and year/month fixed effects, respectively and u is the error term all in day d and district i. Standard errors are clustered at the district level.

All our specifications include district and year-month fixed effects. The estimates of the effect of temperature on daily crime rates are then identified from the short-term fluctuations in daily temperatures within the district and year-months, thus removing unobserved heterogeneity between districts as well

[6] Available http://portal.chmi.cz/informace-pro-vas/prezentace-a-vyuka/SIVS

as district-specific seasonality of crime rates.

The Czech Republic is a country with a low number of homicides[1] compared to other countries (Nováček (2015)). This inevitably means that the majority (99.55%) of observations equals to zero. Statistics of sexual crimes also equal zero in 96.41 % of observations.[2] For this reason, I use Poisson regression instead of OLS when I estimate the impact of weather on the number of homicides and sexual crimes.

4.2 Limitations of empirical methods

I acknowledge several limitations of my empirical methods:

1) Police data might suffer from delayed reporting. For example, property crimes are often reported with a delay. A similar problem holds for some types of assaults, particularly domestic violence, where the victim reports the last attack of the criminal, which is often not the only one. In other words, for assaults committed in domestic violence we know only the date of the last attack, but we have no statistical evidence about the previous attacks. However, the majority of crimes (primarily violent crimes) are reported on the day of the criminal activity (Horrocks & Menclova (2011)).
2) Sometimes the date of offense is unknown. In such cases police officers frequently entered the date of crime committed as 1st of January. I dropped all 1st of January from the analysis.[3]
3) There seems to be several issues in constructing weather variables. As already discussed in subsection 3.4, I do not have data from each district, but I have to rely on weather data from 10 meteorological stations. Therefore I provide several robustness checks on this issue. Specifically, I have split the data into summer and winter months and estimate my regression on each separately (see A.1.4 in the Appendix). These results suggest that the effect of temperature on sexual crimes and assaults is different in summer and winter

[1] Recall Figure 3.1 and Figure 3.2 for details.

[2] Horrocks & Menclova (2011) use the OLS method to estimate their regressions because they claim that both violent crime and property crime series are stationary. Because the dependent variable equals zero in 2.5% of the sample, which is caused by days with no crime, they use the Tobit model for a robustness check. Because they detected only a marginal difference on the dependent variable when using OLS and the Tobit approach, they argue that there is no bias when using OLS due to the value zero in the dependent variable.

[3] Such misreporting seems not to be correlated with weather.

months. No such result was found for other crime categories.

Moreover, given that Czech law considers an outdoor temperature higher than 26'C extreme (recall the discussion in subsection 3.4), I test the impact of the 26'C temperature threshold on my data (see A.1.5 in the appendix). I also use the maximum daily instead of the daily mean temperature as an independent variable (see A.1.1 in the Appendix). Finally I compute the mean temperature and total precipitations in the district as an average from the three nearest meteorological stations (for regressions results see A.1.2 in the Appendix).

4) I estimate the short-term effects of weather on crime within months and between districts within a month. This way, I am able to isolate unobservable factors that affect crime and vary between districts and between different years and seasons within a year. The estimates thus have a causal interpretation. However, they should be interpreted as the causal effects of short-term weather fluctuations. Admittedly, this data and methodology is unable to identify the long-term effects of weather changes, e.g. climate change.

5) Regressions estimating the impact of weather on homicides, robberies and all regression made on crime investigation suffer from R^2 below 0.1. This issue common existing literature on a similar topic (most notably Horrocks & Menclova (2011)) However, I do not use our models to predict future criminality, but primarily to estimate the link between temperature and/or precipitation and crime. What is important is to avoid endogeneity, not to include all the factors that might explain criminal behavior.

6) There might be a possible spatial endogeneity in our data. Imagine a criminal gang that operates in Prague, but also in districts near Prague. We are not able to capture these phenomena. Authors of other studies on a similar topic have also faced this issue. Horrocks & Menclova (2011) argue that:

"We have not explicitly dealt with this issue but we take some comfort in the large size of police districts (average population of 94,600) and thus believe that spatial correlation does not have significant implications for our results. If police districts were city blocks, then it would be far more likely for a wave of burglaries to affect a cluster of city blocks. However, as our police districts are far larger than this, spatial correlation is unlikely to be a major issue."

Despite the above limitations and challenges mentioned above, I believe the data and my methodology allow a sufficiently credible identification of the causal link between weather and crime in the Czech Republic.

Results

In this section, I present results of models that examine the link between different crimes and weather (temperature and/or rain). I focus on five types of criminal activity - homicides, sexual crimes, assaults, thefts, and robberies[1].

The estimated effects of heat and precipitation on crime are summarized graphically in Figure 5.1 and Figure 5.2, respectively.

To conclude, at a sufficient significance level, I find that temperature has a positive effect on the total number of daily sexual crimes, assaults, thefts, and robberies. Rain has a negative and significant effect on the total number of assaults. No statistical significance of heat or rain is detected for homicide data. However, according to Chersich *et al.* (2019), only half of published studies on the link between heat and homicides found statistically significant results.

Estimates in Table 5.1 suggests that temperature has a non significant negative impact on the number of homicides. My results suggest that there is a non-significant positive relationship between precipitation and the number of homicides.

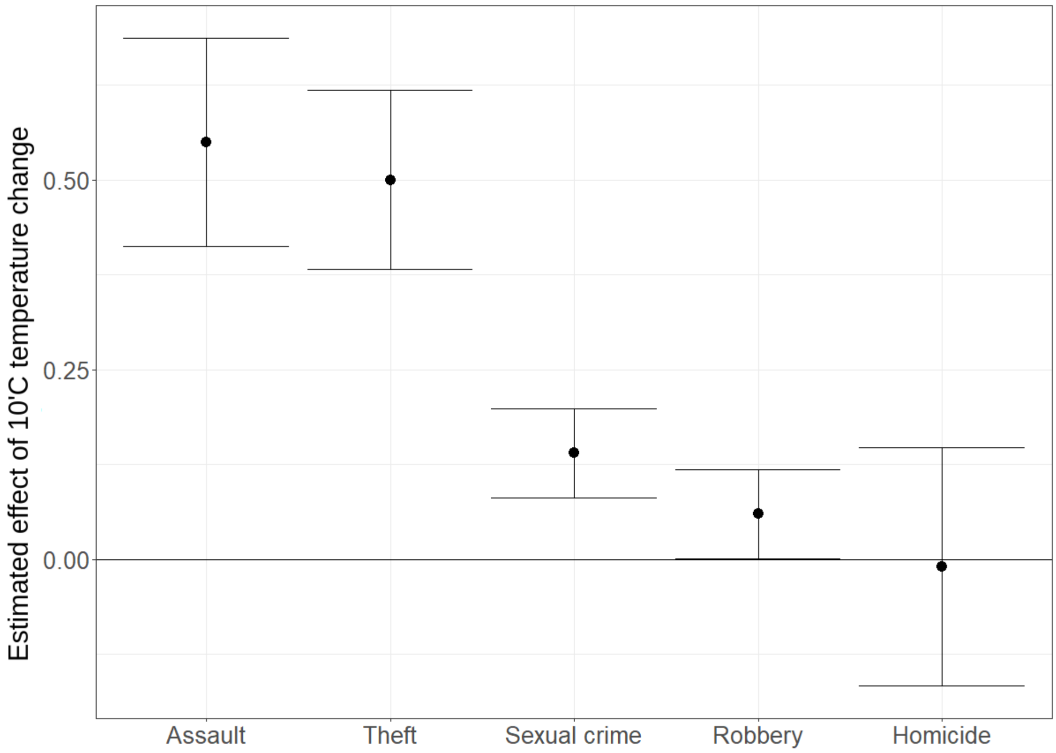
To summarize the effect of temperature on sexual crimes, as displayed in Table 5.2, Columns 1 and 2, temperature has a positive significant effect on the number of sexual crimes. Moreover, the effect is linear, not quadratic. Column 3 shows that there is a non-significant negative link between precipitation and number of sexual crimes committed.

My results on temperature seem not to be surprising because existing studies found a similar effect of heat on rapes and sexual crimes in general (for example Gamble & Hess (2012)).

Blatníková *et al.* (2015) argue that 38.4% of sexual crimes in the Czech Republic is committed outside. Our results therefore seem to be consistent

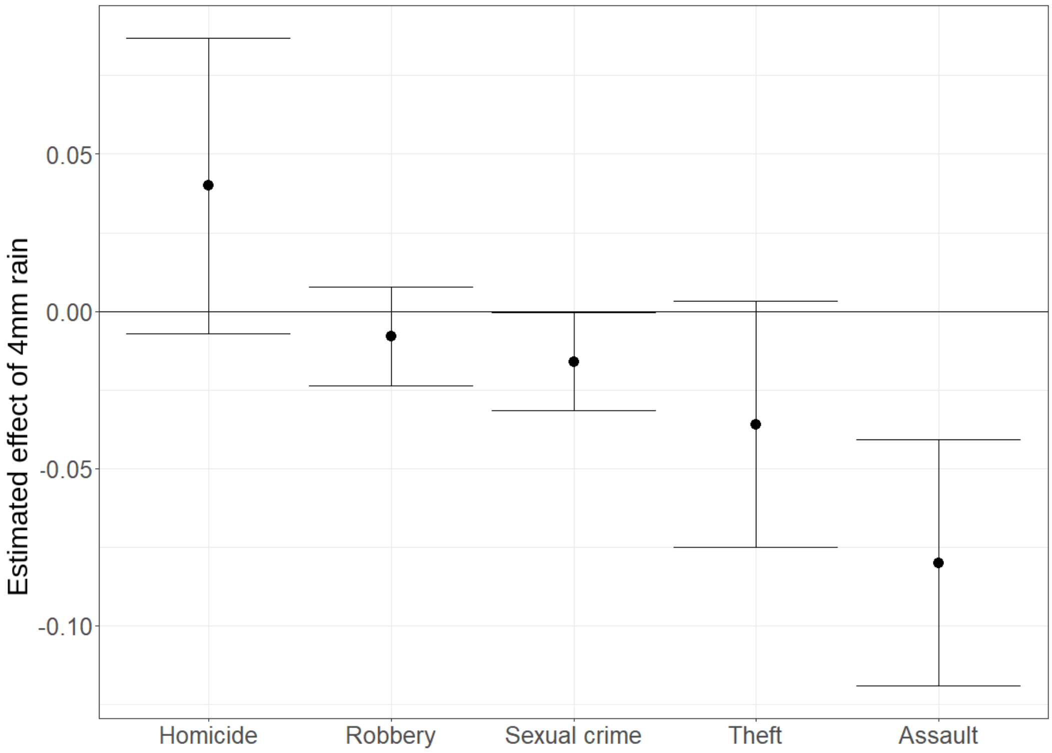
[1] The link between weather and fraud is examined for the purpose of a robustness check. See more in Section 5.1

Figure 5.1: Effect of 10'C increase in temperature



Source: Author. Estimates from specification (5). Plot of effects of 10'C temperature increase on the change of crime rates per 1.000.000 people. Vertical lines stand for 95 % confidence intervals.

Figure 5.2: Effect of 4 mm increase in rain



Source: Author. Estimates from specification (7). Plot of effects of 4 mm rain on the change of crime rates per 1.000.000 people. Vertical lines stand for 95 % confidence intervals.

Table 5.1: Estimates: Homicides - Poisson regression.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Temperature$	-0.001	-0.02*		-0.009
	(0.008)	(0.01)		(0.008)
$Temperature^2$		0.0006		
		(0.0004)		
$Rain$			0.01*	0.01
			(0.006)	(0.009)
$Rain \cdot Temperature$				-0.0002
				(0.0007)
Intercept	-2.404***	-2.359***	-2.368***	-2.358***
	(0.417)	(0.433)	(0.431)	(0.429)
N	451185	451185	451185	451185
Pseudo R^2	0.01	0.01	0.01	0.01

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

with our expectations. During rainy days people prefer to stay home, which decreases the likelihood of outdoor sexual crimes. Moreover, scholars such as Brabenec & Montag (2018) test the hypothesis if criminal behavior is a rational decision driven by gains from crime. This hypothesis might be applicable for sexual crimes where people enjoy sex more on summer days, thus implying higher *non-pecuniary gains from crime.*

Temperature has a linear positive effect on the number of assaults committed. However, we cannot say that there is a quadratic relationship between heat and assaults.

From the result in Column 3, we can argue that rain has a negative effect on the total number of assaults committed.

Based on Table 2.1 we argue that temperature has a positive significant effect on number of assaults committed, which is consistent with previous studies. Our estimates confirm this pattern in the Czech context.

Table 5.2: Estimates: Sexual crimes - Poisson regression.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Temperature	0.014***	0.012***		0.015***
	(0.003)	(0.004)		(0.003)
$Temperature^2$		0.0001		
		(0.0002)		
Rain			-0.004**	0.004
			(0.002)	(0.005)
$Rain \cdot Temperature$				-0.0006*
				(0.0003)
Intercept	-1.671***	-1.677***	-1.656***	-1.679***
	(0.18)	(0.179)	(0.179)	(0.180)
N	471647	471647	471647	471647
Pseudo R^2	0.16	0.16	0.16	0.16

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
Year_month dummy, weekday & holidays dummy and district dummy.
The dependent variable is the number of sexual crimes per 1.000.000 population.

Table 5.3: Estimates: Assaults

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Temperature$	0.055***	0.049***		0.054***
	(0.007)	(0.008)		(0.006)
$Temperature^2$		0.0004		
		(0.0003)		
$Rain$			-0.02***	-0.03***
			(0.005)	(0.008)
$Rain \cdot Temperature$				0.0006
				(0.0006)
Intercept	2.544***	2.532***	2.617***	2.588***
	(0.239)	(0.239)	(0.239)	(0.239)
N	479295	479294	479295	479293
R^2	0.15	0.15	0.15	0.15
F test p-value	0.00	0.00	0.00	0.00

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

The negative effect of rain on assaults seems to be explainable in a similar way as we explained the effect of precipitation on sexual crimes. When people stay home, they are less likely to become victims of assaults. Hough & Mayhew (1983) and Van Dijk *et al.* (1990) arrived at the same conclusion in their studies. Moreover, lower social interaction between people on rainy days has similar effect.

Column 4 shows, that in the case of assaults, there is no statistically significant interaction between rain and temperature.

The estimates for sexual crimes and assaults are robust. The robustness can be observed when we compare results from Columns 1-4 and also when we compare estimates of the mean daily temperature with robustness checks in the Appendix (see subsection A.1).

Table 5.4: Estimates: Thefts

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Temperature$	0.05***	0.058***		0.043***
	(0.006)	(0.008)		(0.006)
$Temperature^2$		-0.0007**		
		(0.0003)		
$Rain$			-0.009*	-0.038***
			(0.005)	(0.01)
$Rain \cdot Temperature$				0.002***
				(0.0007)
Intercept	5.993***	6.012***	6.039***	6.046***
	(0.254)	(0.254)	(0.254)	(0.254)
N	491309	491309	491309	491309
R^2	0.63	0.63	0.63	0.63
F test p-value	0.00	0.00	0.00	0.00

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

Thefts, as displayed in Table 5.4, are the only pure property crimes analyzed in this paper. The OLS models for thefts have much higher R^2 (0.6) than for other crimes. This is so because district dummy variables explain much of the variance of the dependent variable. Moreover, only 38.57% of observations is equal to zero, which provides a good variation in the data.

Column 2 suggest that there is a positive quadratic relationship between temperature and the total number of thefts. This finding is supported also by existing studies, e.g. Horrocks & Menclova (2011).

According to estimates in Column 3, rain has a negative impact on the total number of thefts committed. However, Column 3 has the only statistical significant estimate has the and only at the 10% significance level.

Thefts are the only crime category where we find an interaction between rain and temperature. In other words, not only do temperature and precipitation matter, but it is important to consider heat and rain together (see Model 4)[2].

Robbery is not a frequent type of a criminal activity in the Czech Republic. In our dataset of robberies, 91.66 % of observation equals to zero.

Columns 1 suggest that there is significant evidence that heat impacts the number of robberies committed. However, the results from Column 1 is significant only at the 10% level.

Columns 3 shows no statistical significant evidence between the precipitations and the number of robberies. Moreover, according to Column 4, there does not appear to be any interaction between rain and temperature on robbery data. When I compare our results with previous studies, our results are not an exception. Ranson (2014) also did not find any statistical significance between precipitation and robberies, and he also had difficulty finding a good significance level between heat and robberies.

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[2]For a detailed study of the interaction between rain and temperature on different types of criminal activity see Ranson (2014)

Table 5.5: Estimates: Robberies

Variable	(1)	(2)	(3)	(4)
Temperature	0.006*	0.006		0.005*
	(0.003)	(0.004)		(0.003)
Temperature^2		0.000002		
		(0.0002)		
Rain			-0.002	-0.008*
			(0.002)	(0.004)
$Rain \cdot Temperature$				0.0005
				(0.0003)
Intercept	3.56***	3.56***	3.568***	3.572***
	(0.159)	(0.159)	(0.159)	(0.159)
N	471391	471390	471391	471389
R^2	0.05	0.05	0.05	0.05

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

existing studies, e.g. Horrocks & Menclova (2011).

According to estimates in Column 3, rain has a negative impact on the total number of thefts committed. However, Column 3 has the only statistical significant estimate has the and only at the 10% significance level.

Thefts are the only crime category where we find an interaction between rain and temperature. In other words, not only do temperature and precipitation matter, but it is important to consider heat and rain together (see Column 4)[3].

5.1 Robustness checks

In this Section I perform several robustness checks that are motivated by possible limitations of this study as described in the Section 4.2.

Based on results in the Section A.4.1 I argue that there no significant difference between mean and maximum daily temperature effect on crime.[4] According to results in the Section A.4.2, there is no difference if I use a mean daily temperature from the three nearest stations as an explanatory variable, or data from the nearest station. Therefor it seems that my data do not suffer from temperature measurement error due to low meteorological station cover.

In the Section A.4.3 I check if there is a significant link between temperature/rain and frauds. Because of the insignificant results I argue that results in this article are not caused by spurious regression. Same results arise from the Section A.4.5 where I used 26'C temperature threshold as an explanatory variable. In this robustness check, significant results was found for sexual crimes and assaults which is consistent with main findings in this article. On the other hand, no such significance has been found in property crimes (thefts and robberies).

To ensure, that my results do not suffer from spatial endogeneity, I cluster standard errors at the region levels (in the main regression all standard errors are clustered on the district level). Except thefts, there is no substantial change in the standard errors in the tables A.27 and A.28 compared to the main regressions. Therefor I suppose that my estimates do not suffer from the spatial

[3]For a detailed study of the interaction between rain and temperature on different types of criminal activity see Ranson (2014)

[4]The significance remained the same, estimated effects are negligibly lower in maximum daily estimates.

bias. For thefts, see equation 3 and 4 in the table A.28, it seems that main results might be impacted be spatial dependencies in the data. Following argumentation by Horrocks & Menclova (2011), I suppose this is because of strong relationship between specific districts and thefts. This conclusion is supported also by high R^2 in thefts regression.

Only a few authors have asked if the effect of temperature on crime should be interpreted as an increase in the total number of crimes, or as a substitution effect from cold days to hot days. This issue was solved primarily by authors that focused on the long term impact of heat on crime (most notably Ranson (2014)). However, this question is relevant also for the short term analysis.

My test has the following structure. I constructed monthly temperature averages per each region over a period of years. If the daily temperature in day d and region r is higher than the monthly average in the same region, I consider the day "hot". Otherwise the day is "cold". Hot and cold days are not changing regularly. If the effect of temperature on crime is predominantly a substitution effect from cold days to hot days rather than an increase in the total number of crimes, then my estimates on hot days should be higher than my estimates on cold days. On the other hand, if the temperature causes an increase in the total number of crimes, then I should observe a similar increase in the total number of crimes on hot and cold days.

The results in section A.4.6 suggest that in the case sexual crimes, there is rather a substitution effect from cold days to hot days. However, temperature seems to cause a real increase in assaults and thefts. In other words, if the day d had not been hot, no additional assaults or thefts would have been committed. The different results of sexual crimes in hot and cold days, and winter and summer months, as displayed in the tables A.19 and A.20 and the table A.14, respectively, might be explained by different sex behavior in hot and cold weather. According to Markey & Markey (2013) or Wellings *et al.* (1999), people have more sexual activity in the summer. Therefor my estimates of sexual crimes are higher in the summer time than in the winter.

Conclusion

The evidence assembled in this paper suggests that weather is an important factor that determines crime rates. In particular, temperature has a significant positive effect on the total number of assaults, thefts and sexual crimes. The analysis does not provide evidence about the number of robberies and homicides recorded. Moreover, total daily precipitation causes the number of assaults and sexual crimes to decrease significantly. This cannot be said about any other crime activity.

Despite the limitations that my empirical work has, several policy implication can be drawn from my results. Firstly, if the police want to lower the crime rate then they should adapt their patrol tactics to the weather. For example, additional patrols could conducted on warm days, at the expense of cold days. The police should take into consideration not only seasonal characteristics (e.g. winter or summer), but also the short-term weather forecast. Moreover, because one of the possible explanation of how weather effects crime builds on the relationship between heat and alcohol consumption, policy makers might consider more regulation of alcohol sale.

To conclude, my study makes several valuable contributions. Most importantly, using a large and detailed dataset, I demonstrate that the link between weather and crime is present also in Central Europe, specifically in the Czech Republic. Moreover, my results are consistent with the current academic literature and with theoretical frameworks.

Last, not least, my results might have climate change implications. To the extend that the estimates can be interpreted as an overall increase in crime rather than substitution from cold to warm day (which the results in section A.4.6 indicates for several crime categories) then the results also suggest broader negative consequences of climate change on crime. However, further research is needed to confirm and expand on these findings.

Bibliography

Anderson, C. A. (1989): "Temperature and aggression: ubiquitous effects of heat on occurrence of human violence." *Psychological bulletin* **106(1)**: p. 74.

Anderson, C. A., K. B. Anderson, N. Dorr, K. M. DeNeve, & M. Flanagan (2000): "Temperature and aggression." In "Advances in experimental social psychology," volume 32, pp. 63–133. Elsevier.

Baryshnikova, N., S. F. Davidson, D. Wesselbaum *et al.* (2019): "Do you feel the heat around the corner? the effect of weather on crime." *Technical report*.

Blakeslee, D. & R. Fishman (2014): "Weather shocks, crime, and agriculture: evidence from india." *Social Science Research Network* .

Blatníková, v., P. Faridová, & P. Zeman (2015): "Znásilnění v Čr -trestné činy a odsouzení pachatelé." *Institut pro kriminologii a sociální prevenci* .

Brabenec, T. & J. Montag (2018): "Criminals and the price system: Evidence from czech metal thieves." *Journal of Quantitative Criminology* **34(2)**: pp. 397–430.

Burrows, K. & P. L. Kinney (2016): "Exploring the climate change, migration and conflict nexus." *International journal of environmental research and public health* **13(4)**: p. 443.

Caneppele, S. & M. F. Aebi (2019): "Crime drop or police recording flop? on the relationship between the decrease of offline crime and the increase of online and hybrid crimes." *Policing: A Journal of Policy and Practice* **13(1)**: pp. 66–79.

Card, D. & G. B. Dahl (2011): "Family violence and football: The effect of unexpected emotional cues on violent behavior." *The quarterly journal of economics* **126(1)**: pp. 103–143.

Chersich, M. F., C. P. Swift, I. Edelstein, G. Breetzke, F. Scorgie, F. Schutte, & C. Y. Wright (2019): "Violence in hot weather: Will climate change exacerbate rates of violence in south africa?" *SAMJ: South African Medical Journal* **109(7)**: pp. 447–449.

Coccia, M. (2017): "A theory of general causes of violent crime: Homicides, income inequality and deficiencies of the heat hypothesis and of the model of clash." *Aggression and Violent Behavior* **37**: pp. 190–200.

Cornish, D. B. & R. V. Clarke (2014): "The reasoning criminal: Rational choice perspectives on offending." .

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

Glaeser, E. L., B. Sacerdote, & J. A. Scheinkman (1996): "Crime and social interactions." *The Quarterly journal of economics* **111(2)**: pp. 507–548.

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

Hough, M. & P. Mayhew (1983): *The British crime survey: first report*, volume 76. HM Stationery Office Ixindon.

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

Markey, P. M. & C. N. Markey (2013): "Seasonal variation in internet keyword searches: a proxy assessment of sex mating behaviors." *Archives of sexual behavior* **42(4)**: pp. 515–521.

McDowall, D., C. Loftin, & M. Pate (2012): "Seasonal cycles in crime, and their variability." *Journal of Quantitative Criminology* **28(3)**: pp. 389–410.

Miles-Novelo, A. & C. A. Anderson (2019): "Climate change and psychology: Effects of rapid global warming on violence and aggression." *Current Climate Change Reports* **5(1)**: pp. 36–46.

NOVÁČEK, A. (2015): "Vraždy ve světě: makroregionální srovnání." *Geografické rozhledy* **24**: pp. 8–9.

OTRACHSHENKO, V., O. POPOVA, & J. TAVARES (2021): "Extreme temperature and extreme violence: evidence from russia." *Economic Inquiry* **59(1)**: pp. 243–262.

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

SEKHRI, S. & A. STOREYGARD (2014): "Dowry deaths: Response to weather variability in india." *Journal of development economics* **111**: pp. 212–223.

SOBIŠEK, B. (1993): "Meteorologicky slovnik vykladovy a terminologicky." *Akademia, Ministerstvo životniho prostřeni ČR, Praha, ss* **594**.

VAN DIJK, J. J., P. MAYHEW, & M. KILLIAS (1990): *Experiences of crime across the world: Key findings from the 1989 International Crime Survey.* Brill Archive.

WELLINGS, K., W. MACDOWALL, M. CATCHPOLE, & J. GOODRICH (1999): "Seasonal variations in sexual activity and their implications for sexual health promotion." *Journal of the Royal Society of Medicine* **92(2)**: pp. 60–64.

WHITE, H. (1980): "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity." *Econometrica: journal of the Econometric Society* pp. 817–838.

Appendix

A.1 Additional figures

Figure A.1: Seasonal pattern of crime: monthly.

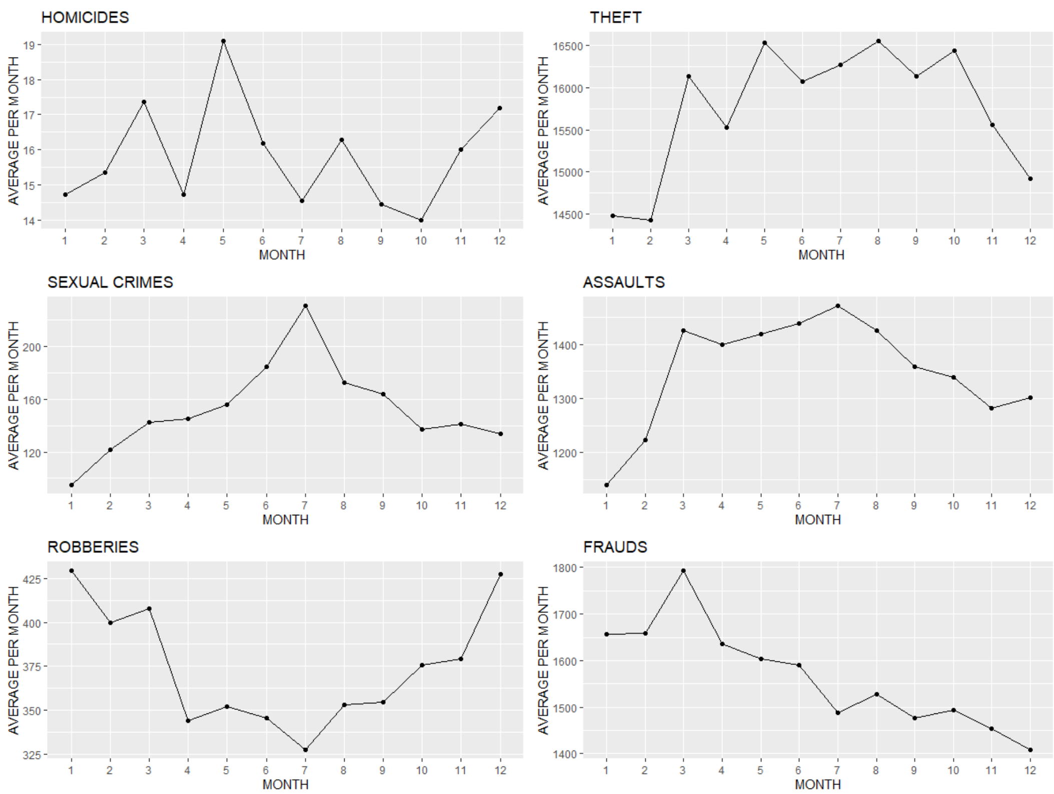


Figure A.1 confirms that crime data have a strong seasonal patterns. Except homicides, robberies and frauds, all other categories of crimes were less often committed in January.

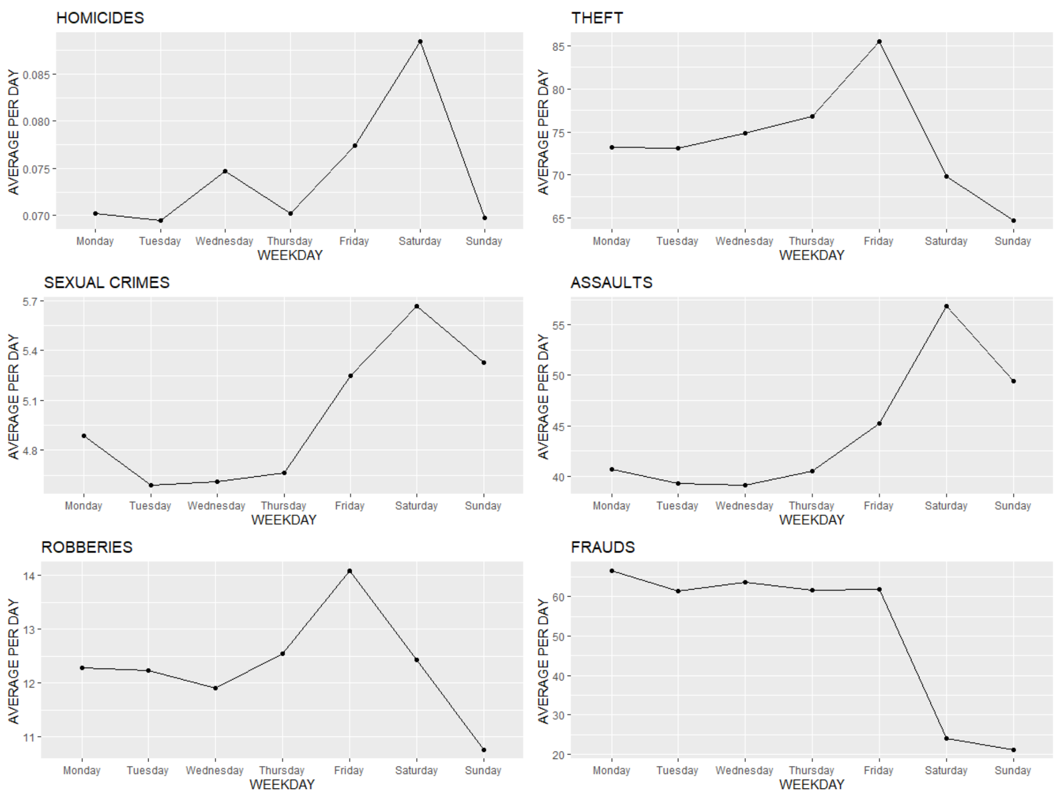
Although that according to McDowall *et al.* (2012) seasonal crime patterns have been investigated in criminological research for more than a century, in Czech Republic is this issue on the brink of attention of academics. Therefore I have to rely primarily on foreign studies.

McDowall *et al.* (2012) argue that *"The existence of seasonal patterns is not explainable by monthly temperature differences between areas, but seasonality and temperature variations do interact with each other."* In other words, authors say that monthly fluctuations have both environmental and social components. McDowall *et al.* (2012) claim that all major types of crime follow a seasonal pattern. Moreover they suggest that not controlling for months, but also controlling for weekdays is important to identify crime seasonal components.

See Figure A.2 for a graph that shows sums of crimes committed by each day of the week.

Sexual crimes and assaults are committed more often on weekends compared to other days. On the other hand, frauds and thefts are less frequently committed during Saturdays and Sundays. Moreover, maximum number of thefts and burglaries is committed on Friday.

Figure A.2: Seasonal pattern of crime: by day of the week.



A.2 Additional tables

Table A.1: Categories of crime data

Available Aggregated Data	Corresponding TSK number
Homicide	101 - 106
Theft	311, 312, 321 - 324, 331, 332, 341, 350, 351, 371 - 373, 390, 411 - 413, 421, 431 - 435, 441, 451, 461, 462, 471, 480, 490
Sexual	201, 202, 211, 212, 231
Assault	111 - 116, 121, 122, 141 - 143, 151, 161, 171 - 174, 181 - 190
Robbery	131, 132
Fraud	511, 522, 530, 830, 880 - 882

Table A.2: Meteorological stations matched to Regions

Region	Meteorological station
Prague	Average of Praha Ruzyně and Praha Libuš
Central Bohemia Region	Average of Praha Ruzyně and Praha Libuš
South Bohemia Region	Kocelovice
Pilsen Region	Přimda
Ústí nad Labem Region	Milešovka
Hradec Králové Region	Liberec
South Moravia Region	Brno Tuřany
Moravian-Silesian	Mošnov
Olomouc Region	Mošnov
Zlín Region	Lysá Hora
Vysočina Region	Přibyslav
Pardubice Region	Přibyslav
Liberec Region	Liberec
Karlovy Vary Region	Přimda

A.3 Year and Month dummies

Table A.3: Estimates: Homicides - Poisson regression.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Temperature$	-0.0006	-0.01		0.001
	(0.008)	(0.01)		(0.008)
$Temperature^2$		0.0007*		
		(0.0004)		
$Rain$			0.007	0.01
			(0.006)	(0.008)
$Rain \cdot Temperature$				-0.00007
				(0.0007)
Intercept	-2.830***	-2.874***	-2.839***	-2.839***
	(0.223)	(0.224)	(0.223)	(0.223)
N	451185	451185	451185	451185
Pseudo R^2	0.09	0.09	0.09	0.09

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
Year dummy, month dummy, weekday & holidays dummy and district dummy.
The dependent variable is the number of homicides per 1.000.000 population.

Table A.4: Estimates: Sexual crimes - Poisson regression.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Temperature	0.014***	0.011***		0.015***
	(0.003)	(0.004)		(0.003)
$Temperature^2$		0.0002		
		(0.0002)		
Rain			-0.004**	0.004
			(0.002)	(0.005)
$Rain \cdot Temperature$				-0.0005
				(0.0003)
Intercept	-1.618***	-1.626***	-1.624***	-1.622***
	(0.088)	(0.088)	(0.088)	(0.088)
N	471647	471647	471647	471647
Pseudo R^2	0.16	0.16	0.16	0.16

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
Year dummy, month dummy, weekday & holidays dummy and district dummy.
The dependent variable is the number of sexual crimes per 1.000.000 population.

Table A.5: Estimates: Assaults

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Temperature$	0.053***	0.048***		0.052***
	(0.005)	(0.006)		(0.005)
$Temperature^2$		0.0004		
		(0.0003)		
$Rain$			-0.024***	-0.03***
			(0.005)	(0.008)
$Rain \cdot Temperature$				0.0006
				(0.0006)
Intercept	1.914***	1.897***	1.891***	1.158***
	(0.12)	(0.12)	(0.12)	(0.12)
N	479405	479404	479405	479403
R^2	0.15	0.15	0.15	0.15

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
Year dummy, month dummy, weekday & holidays dummy and district dummy.
The dependent variable is the number of assaults per 1.000.000 population.

Table A.6: Estimates: Thefts

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Temperature	0.05***	0.069***		0.047***
	(0.006)	(0.007)		(0.006)
$Temperature^2$		-0.001***		
		(0.0003)		
Rain			-0.008	-0.033***
			(0.005)	(0.01)
$Rain \cdot Temperature$				0.002***
				(0.0007)
Intercept	5.515***	5.578***	5.477***	5.551***
	(0.129)	(0.13)	(0.129)	(0.129)
N	491420	491420	491420	491420
R^2	0.63	0.63	0.63	0.63

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
Year dummy, month dummy, weekday & holidays dummy and district dummy.
The dependent variable is the number of thefts per 1.000.000 population.

Table A.7: Estimates: Robberies

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Temperature$	0.006**	0.005		0.005*
	(0.003)	(0.004)		(0.003)
$Temperature^2$		0.000006		
		(0.0002)		
$Rain$			-0.002	-0.008*
			(0.002)	(0.004)
$Rain \cdot Temperature$				0.0005*
				(0.0003)
Intercept	3.241***	3.238***	3.237***	3.249***
	(0.08)	(0.08)	(0.08)	(0.08)
N	471501	471500	471501	471499
R^2	0.05	0.05	0.05	0.05

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
Year dummy, month dummy, weekday & holidays dummy and district dummy.
The dependent variable is the number of robberies per 1.000.000 population.

A.4 Robustness checks

A.4.1 Maximum daily temperature

Table A.8: Estimates: Homicides - Poisson regression. Maximum daily temperature.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Temperature	-0.0008	-0.018		-0.0002	-0.01	-0.026**		-0.009
	(0.007)	(0.01)		(0.007)	(0.007)	(0.012)		(0.007)
$Temperature^2$		0.0007*				0.0007*		
		(0.0003)				(0.0004)		
Rain			0.007	0.008			0.01*	0.01
			(0.006)	(0.01)			(0.006)	(0.01)
$Rain \cdot Temperature$				-0.00006				-0.00009
				(0.0006)				(0.0006)
Intercept	-2.830	-2.836***	-2.839***	-2.840***	-2.376***	-2.361***	-2.368***	-2.397***
	(0.223)	(0.223)	(0.223)	(0.222)	(0.417)	(0.417)	(0.431)	(0.411)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	451185	451185	451185	451185	451185	451185	451185	451185
Pseudo R^2	0.09	0.09	0.09	0.09				

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 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 A.9: Estimates: Sexual crimes - Poisson regression. Maximum daily temperature.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Temperature	0.012***	0.009**		0.013***	0.012***	0.009**		0.013***
	(0.002)	(0.004)		(0.002)	(0.003)	(0.005)		(0.18)
$Temperature^2$		0.0001				0.00009		
		(0.0001)				(0.0001)		
Rain			-0.004	0.008*			-0.004	0.008*
			(0.002)	(0.005)			(0.002)	(0.005)
$Rain \cdot Temperature$				-0.0004**				-0.0007***
				(0.0003)				(0.0003)
Intercept	-1.650***	-1.649***	-1.624***	-1.661***	-1.706***	-1.702***	-1.656***	-1.721***
	(0.088)	(0.088)	(0.088)	(0.088)	(0.180)	(0.180)	(0.179)	(0.003)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	471647	471647	471647	471647	471647	471647	471647	471647
Pseudo R^2	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16

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

Table A.10: Estimates: Assaults. Maximum daily temperature.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Temperature$	0.047***	0.044***		0.045***	0.048***	0.042***		0.046***
	(0.005)	(0.008)		(0.005)	(0.005)	(0.009)		(0.005)
$Temperature^2$		0.0001				0.0002		
		(0.0002)				(0.0003)		
$Rain$			-0.024***	-0.024***			-0.02***	-0.025***
			(0.005)	(0.009)			(0.005)	(0.009)
$Rain \cdot Temperature$				0.0002				0.0002
				(0.0005)				(0.0005)
Intercept	1.784***	1.784***	1.891***	1.813***	2.409***	2.418***	2.617***	2.451***
	(0.121)	(0.121)	(0.12)	(0.121)	(0.239)	(0.239)	(0.239)	(0.24)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	479405	479404	479405	479403	479295	479294	479295	479293
R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 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 A.11: Estimates: Thefts. Maximum daily temperature.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Temperature	0.031***	0.069***		0.028***	0.027***	0.05***		0.023***
	(0.005)	(0.008)		(0.005)	(0.005)	(0.009)		(0.005)
$Temperature^2$		-0.001***				-0.0009***		
		(0.0003)				(0.0003)		
Rain			-0.008	-0.032***			-0.009*	-0.039***
			(0.005)	(0.011)			(0.005)	(0.011)
$Rain \cdot Temperature$				0.0016***				0.002***
				(0.0006)				(0.0006)
Intercept	5.414***	5.407***	5.477***	5.453***	5.928***	5.892***	6.039***	5.989***
	(0.129)	(0.129)	(0.129)	(0.129)	(0.255)	(0.255)	(0.254)	(0.255)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	491420	491420	491420	491420	491309	491309	491309	491309
R^2	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 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 A.12: Estimates: Robberies. Maximum daily temperature.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Temperature$	0.004*	0.003		0.003	0.004	0.004		0.003
	(0.002)	(0.004)		(0.002)	(0.003)	(0.005)		(0.003)
$Temperature^2$		0.00003				-0.00001		
		(0.0001)				(0.0001)		
$Rain$			-0.002	-0.009**			-0.002	-0.01**
			(0.002)	(0.004)			(0.002)	(0.004)
$Rain \cdot Temperature$				0.0005**				0.0005*
				(0.0002)				(0.0002)
Intercept	3.228***	3.228***	3.237***	3.24***	3.549***	3.549***	3.568***	3.565***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.159)	(0.159)	(0.159)	(0.159)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	471501	471500	471501	471499	471391	471390	47391	47389
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

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

A.4.2 Average from three nearest stations

Table A.13: Estimates: Homicides - Poisson regression. Mean daily temperature from three nearest stations.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Temperature$	0.003	-0.008		0.004	0.001	-0.01		0.002
	(0.008)	(0.01)		(0.009)	(0.009)	(0.01)		(0.009)
$Temperature^2$		0.0008*				0.0008		
		(0.0005)				(0.0005)		
$Rain$			-0.0002	0.016			0.0002	0.01
			(0.008)	(0.02)			(0.009)	(0.02)
$Rain \cdot Temperature$				-0.001				-0.001
				(0.001)				(0.001)
Intercept	-2.827***	-2.865***	-2.831***	-2.844***	-2.356***	-2.376***	-2.355***	-2.372***
	(0.224)	(0.224)	(0.223)	(0.222)	(0.432)	(0.433)	(0.430)	(0.423)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	451185	451185	451185	451185	451185	451185	451185	451185
Pseudo R^2	0.09	0.09	0.09	0.09	0.1	0.1	0.1	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 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 A.14: Estimates: Sexual crimes - Poisson regression. Mean daily temperature from three nearest stations.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Temperature	0.014***	0.011***		0.015***	0.14***	0.011**		0.015***
	(0.003)	(0.004)		(0.003)	(0.003)	(0.004)		(0.003)
$Temperature^2$		0.0002				0.0002		
		(0.0002)				(0.0002)		
Rain			-0.006**	0.006			0.007**	0.007
			(0.003)	(0.007)			(0.003)	(0.007)
$Rain \cdot Temperature$				-0.0009*				-0.0009**
				(0.0004)				(0.0004)
Intercept	-1.616***	-1.625***	-1.621***	-1.622***	-1.672***	-1.676***	-1.652***	-1.681***
	(0.088)	(0.088)	(0.088)	(0.088)	(0.179)	(0.179)	(0.179)	(0.18)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	471647	471647	471647	471647	471647	471647	471647	471647
Pseudo R^2	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16

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

Table A.15: Estimates: Assaults. Mean daily temperature from three nearest stations.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Temperature$	0.056***	0.049***		0.05***	0.058***	0.05***		0.058***
	(0.005)	(0.007)		(0.006)	(0.006)	(0.008)		(0.006)
$Temperature^2$		0.0004				0.0005		
		(0.0003)			(0.0004)			
$Rain$			-0.03***	-0.02*			-0.025***	-0.02*
			(0.006)	(0.01)			(0.006)	(0.01)
$Rain \cdot Temperature$				-0.0001				-0.00008
				(0.0008)				(0.0008)
Intercept	1.921***	1.902***	1.892***	1.943***	2.545***	2.534***	2.617***	2.577***
	(0.121)	(0.122)	(0.121)	(0.121)	(0.239)	(0.239)	(0.239)	(0.239)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N								
R^2								

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 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 A.16: Estimates: Thefts. Mean daily temperature from three nearest stations.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Temperature	0.05***	0.072***		0.049***	0.047***	0.059***		0.046***
	(0.006)	(0.008)		(0.008)	(0.006)	(0.009)		(0.006)
$Temperature^2$		-0.001***				-0.0008**		
		(0.0003)				(0.0004)		
Rain			-0.15***	-0.018***			-0.017***	-0.026*
			(0.006)	(0.013)			(0.006)	(0.013)
$Rain \cdot Temperature$				0.0004***				0.0007***
				(0.0009)				(0.0009)
Intercept	5.52***	5.584***	5.484***	5.539***	6.00***	6.014***	6.048***	6.03***
	(0.129)	(0.13)	(0.129)	(0.129)	(0.254)	(0.254)	(0.254)	(0.254)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	491420	491420	491420	491420	491309	491309	491309	491309
R^2	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 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 A.17: Estimates: Robberies. Mean daily temperature from three nearest stations.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Temperature	0.005*	0.005		0.005	0.005	0.005		0.004
	(0.003)	(0.004)		(0.003)	(0.003)	(0.005)		(0.003)
$Temperature^2$		0.00003				-0.00002		
		(0.0002)				(0.0002)		
Rain			-0.002	-0.01*			-0.002	-0.01*
			(0.003)	(0.006)			(0.003)	(0.006)
$Rain \cdot Temperature$				0.0007				0.0007
				(0.0004)				(0.0004)
Intercept	3.241***	3.239***	3.237***	3.252***	3.561***	3.561***	3.567***	3.575***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.159)	(0.159)	(0.159)	(0.159)
Year dummies	Y	Y	Y	Y	N	N	N	N
Month dummies	Y	Y	Y	Y	N	N	N	N
Year_Month dummies	N	N	N	N	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	471501	471500	471501	471499	471391	471390	47391	47389
R^2								

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

A.4.3 Frauds

Table A.18: Robustness check - Estimates: Frauds.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Temperature	-0.008	-0.004		-0.007
	(0.006)	(0.01)		(0.006)
$Temperature^2$		-0.0002		
		(0.0004)		
Rain			-0.004	-0.0008
			(0.008)	(0.014)
$Rain \cdot Temperature$				-0.0003
				(0.001)
Intercept	5.118***	5.121***	5.113***	5.119***
	(0.485)	(0.486)	(0.486)	(0.486)
Year_Month dummies	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y
District dummies	Y	Y	Y	Y
N	266842	266842	266842	266842
R^2	0.11	0.11	0.11	0.11
F test p-value	0.00	0.00	0.00	0.00

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

A.4.4 Summer and Winter months

Table A.19: Robustness check - Winter and Summer months

Variable	**Homicides S**	**Homicides W**	**Sexual crimes S**	**Sexual crimes W**	**Assaults S**	**Assaults W**
Temperature	-0.005	-0.002	0.005	0.022**	0.042***	0.07***
	(0.012)	(0.013)	(0.004)	(0.004)	(0.008)	(0.009)
Intercept	-2.315***	-2.192***	-1.543***	-1.360***	2.871***	1.294***
	(0.451)	(0.448)	(0.192)	(0.168)	(0.250)	(0.266)
Year_Month dummies	Y	Y	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y	Y
N	223513	228711	233875	238831	237648	242688
(Pseudo) R^2	0.1	0.1	0.15	0.16	0.15	0.15

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
Each crime category stands for number of crimes per 1,000,000 people.

Table A.20: Robustness check - Winter and Summer months, continue.

Variable	**Thefts S**	**Thefts W**	**Robberies S**	**Robberies W**
Temperature	0.054***	0.04***	0.005	0.008*
	(0.009)	(0.009)	(0.004)	(0.004)
Intercept	6.038***	5.676***	3.623***	2.741***
	(0.268)	(0.288)	(0.170)	(0.149)
Year_Month dummies	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y
District dummies	Y	Y	Y	Y
N	242952	248756	233686	238162
(Pseudo) R^2	0.62	0.65	0.05	0.04

$^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level. Each crime category stands for number of crimes per 1,000,000 people.

A.4.5 Temperature threshold

Table A.21: Robustness check - Threshold of maximum daily temperature 26‘C dummy

Variable	**Homicides**	**Sexual crimes**	**Assaults**	**Thefts**	**Robberies**
Threshold	0.139	0.216***	0.597***	0.122	0.057
	(0.137)	(0.041)	(0.09)	(0.086)	(0.046)
Intercept	-2.359***	-1.667***	2.585***	6.023***	3.558***
	(0.432)	(0.179)	(0.239)	(0.254)	(0.159)
Year_Month dummies	Y	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y	Y
District dummies	Y	Y	Y	Y	Y
N	452225	471647	480462	491310	472452
(Pseudo) R^2	0.1	0.16	0.15	0.63	0.05

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. White (1980) robust SEs in parentheses clustered on a district level.
20‘C corresponds with the 90th quintile of daily mean temperature in the Czech Republic.
Each crime category stands for number of crimes per 1,000,000 people.

A.4.6 Hot and Cold series

Table A.22: Estimates in hot days - Homicides.

Variable	(1)	(2)
Temperature	0.046**	
	(0.02)	
Rain		0.01
		(0.009)
Intercept	-2.157***	-1.985***
	(0.646)	(0.634)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	215617	215617
Pseudo R^2	0.12	0.12

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.23: Estimates in cold days - Homicides

Variable	**(1)**	**(2)**
Temperature	-0.03	
	(0.02)	
Rain		-0.003
		(0.09)
Intercept	-2.854***	-2.735***
	(0.55)	(0.54)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	208792	208792
Pseudo R^2	0.12	0.12

$^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.24: Estimates in hot days - Sexual crimes

Variable	**(1)**	**(2)**
Temperature	0.016**	
	(0.007)	
Rain		0.232***
		(0.004)
Intercept	-1.648***	-1.559***
	(0.234)	(0.232)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	225612	225612
Pseudo R^2	0.17	0.17

$^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.25: Estimates in cold days - Sexual crimes

Variable	**(1)**	**(2)**
Temperature	-0.02**	
	(0.008)	
Rain		0.005
		(0.003)
Intercept	-1.811***	-1.752***
	(0.287)	(0.287)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	218029	218029
Pseudo R^2	0.17	0.17

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.26: Estimates in hot days - Assaults

Variable	**(1)**	**(2)**
Temperature	0.07***	
	(0.015)	
Rain		-0.024***
		(0.007)
Intercept	2.367***	2.684***
	(0.33)	(0.33)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	229167	229167
R^2	0.15	0.15

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.27: Estimates in cold days - Assaults

Variable	**(1)**	**(2)**
Temperature	0.04**	
	(0.15)	
Rain		-0.026***
		(0.007)
Intercept	2.65***	2.554***
	(0.361)	(0.358)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	221500	221500
R^2	0.14	0.14

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.28: Estimates in hot days - Thefts

Variable	**(1)**	**(2)**
Temperature	0.072***	
	(0.016)	
Rain		-0.007
		(0.08)
Intercept	5.923***	6.225***
	(0.356)	(0.35)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	234957	234957
R^2	0.64	0.64

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.29: Estimates in cold days - Thefts

Variable	**(1)**	**(2)**
Temperature	0.061***	
	(0.016)	
Rain		-0.015**
		(0.007)
Intercept	5.772***	5.586***
	(0.384)	(0.38)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	226995	226995
R^2	0.63	0.63

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.30: Estimates in hot days - Robberies

Variable	**(1)**	**(2)**
Temperature	0.016**	
	(0.008)	
Rain		0.001
		(0.004)
Intercept	3.50***	3.561***
	(0.226)	(0.224)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	225357	225612
R^2	0.05	0.05

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.31: Estimates in cold days - Robberies

Variable	**(1)**	**(2)**
Temperature	-0.001	
	(0.008)	
Rain		-0.005*
		(0.003)
Intercept	3.541***	3.549***
	(0.233)	(0.232)
Year_Month dummies	Y	Y
Weekday & holidays	Y	Y
District dummies	Y	Y
N	217774	217774
R^2	0.05	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
White (1980) robust SEs in parentheses clustered on a district level.

Table A.32: Estimates: SE clustered at region levels.

Variable	**Homicides (1)**	**Homicides (2)**	**Sexual crimes (3)**	**Sexual crimes (4)**
Temperature	-0.001		0.014*	
	(0.01)		(0.007)	
Rain		0.01		-0.004**
		(0.01)		(0.002)
Intercept	-2.404***	-2.368***	-1.671***	-1.656***
	(0.453)	(0.444)	(0.239)	(0.238)
Year dummies	N	N	N	N
Month dummies	N	N	N	N
Year_Month dummies	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y
District dummies	Y	Y	Y	Y
N	451185	451185	471647	471647
Pseudo R^2	0.09	0.01	0.16	0.16

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
The dependent variable is the number of homicides and sexual crimes per 1.000.000 population.

Table A.33: Estimates: SE clustered at region levels.

Variable	**Assaults (1)**	**Assaults (2)**	**Thefts (3)**	**Thefts (4)**
Temperature	0.055*		0.05	
	(0.023)		(0.045)	
Rain		-0.02***		-0.009
		(0.007)		(0.01)
Intercept	2.544***	2.617***	5.993***	6.039***
	(0.268)	(0.69)	(1.98)	(2.01)
Year dummies	N	N	N	N
Month dummies	N	N	N	N
Year_Month dummies	Y	Y	Y	Y
Weekday & holidays	Y	Y	Y	Y
District dummies	Y	Y	Y	Y
N	479295	479295	491309	491309
R^2	0.15	0.15	0.63	0.63

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
The dependent variable is the number of assaults and thefts per 1.000.000 population.