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Do You Feel the Heat Around the Corner?

The Effect of Weather on Crime*

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Abstract

In this paper, we study the weather-crime relationship using a unique high-frequency, city-level data set for the United States with 2.4 mio. observations. In contrast to the existing literature using (often) daily data, we match hourly observations of weather and crime.

Our results show that using daily observations overestimates the effect of temperature and underestimates the effect of precipitation on crime and leads to different conclusions about the significance of variables. We document evidence for a non-linear relationship between weather variables and crime. Again, results differ greatly between daily and hourly observations.

Keywords: Crime, Non-linearity, Weather.

JEL codes: C55, K42, Q54.

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1 Introduction

This paper adds to the literature investigating the link between weather and crime.[1] Our research question is whether variables such as temperature, rainfall, or humidity significantly affect crime. Crime represents a large portion of government expenditure, extending to crime deterrents, law enforcement, judicial processing and the housing of criminals. It is estimated that in the 2012 financial year, collectively the local, state and Federal Governments in the United States spent over $280 Billion (U.S. Government Accountability Office, 2017). When including intangible costs of crime, the estimated total annual cost of crime has been as high as $3.41 Trillion (U.S. Government Accountability Office, 2017).

In this paper, we use high-frequency, city-level data to analyze the weather-crime relationship. In contrast to previous papers, we match *hourly* crimes to *hourly* weather measures. This allows a much improved identification of the effects of weather on crime, while increasing the sample size at the same time. Using a low frequency is problematic because averages will hide potentially important variation. Consider the following hypothetical example. Assume that in a city most crimes, for some reason, occur in the morning when it is relatively cold. Using daily weather data and daily number of crime will likely bias the estimate of the effect of weather on crime. We address this important issue by using a much higher-frequency of weather-crime observations.

We construct a unique data set combining crime and weather data with more than 2 million observations. Crime data is collected at the city level over four years (2014-2017) in four major cities in the United States of America. The four cities chosen are Chicago, Indianapolis, Los Angeles, and New York. These cities make up some of the largest cities in the United States by population, whilst differing in other dimensions such as climate and demographic and have been chosen because

[1] Notice that "crime" in this paper should be treated as alleged crime and all suspects are innocent until proven guilty in a court of law.

of data availability and data consistency across cities. For each individually observed crime, we match data from weather stations. The four weather variables studied are temperature, humidity, precipitation, and wind speed. Besides using total crime, we further categorize crime into violent crime (assault and battery, rape, and homicide) and property crime (larceny, robbery, burglary, and grand theft auto). In taking this additional step, we investigate whether weather has different impacts across crime types. We finally investigate non-linear effects of weather and the persistence of the effect of weather conditions on crime.

The previous literature on the link between crime and weather mainly uses a low-frequency of weather and crime variables.[2] Field (1992) uses annual, quarterly, and monthly temperature, precipitation, and sunshine data for England and Wales. He finds that only temperature affects crime. Anderson and DeLisi (2011) use annual data from 1950 to 2008 for violent and non-violent crime in the United States. They find a positive relationship between average annual temperatures and violent crime but not with non-violent crime. Similarly, Tiihonen et al. (2017) use monthly ambient temperatures in Finland and find a positive correlation with violent crime. McDowall et al. (2012) use monthly data for 88 cities in the United States and find that monthly temperature has a positive effect on rape, robbery, assault, burglary, larceny, and motor vehicle theft but not on murder.

Horrocks and Menclova (2011) use daily weather data (maximum and minimum temperature and total precipitation) for New Zealand districts. They find that temperature and rainfall affect violent crimes but only temperature affects property crime. Jacob et al. (2006) also use daily data for minimum and maximum temperature and precipitation. They show that in 116 jurisdictions in the U.S., high crime (violent and property) in one week is followed by less crimes in the next

[2] There also exists a literature using laboratory studies not reviewed here. Anderson (2001) provides an excellent overview.

week. They use weather shocks as an instrument and do not focus on the effects of weather on crime, but on the persistence of crime. Ranson (2014) uses monthly temperature and crime data across U.S. counties. He finds a positive effect of temperature on crime, but no lagged effect. More recently, Heilmann and Kahn (2019) show that total and violent crime increase when daily maximum temperatures exceed 85 degrees Fahrenheit in Los Angeles.

Cohn and Rotton (2000) and later Bushman et al. (2005) use three-hour daily intervals and find a positive correlation between temperature and assaults in Minneapolis. The closest paper to ours is the study by Brunsdon et al. (2009) who combine weather-crime data on an hourly frequency for an urban area of the United Kingdom.[3] There are several differences between our papers. First, our data set is much larger: Brunsdon et al. (2009) use less than 14.000 observations, while we use more than 2 million. Second, the applied methodology is different. Brundson et al. (2009) use the Kent-Joe statistic and a graphical visualization approach. In contrast, we estimate a fixed-effects regression model. Third, we also consider potential non-linear and lagged effects of weather variables.

Several findings stand out. We find important differences in the results for the weather-crime relationship when we use hourly observations rather than daily observations. The literature using daily observations overestimates the effect of temperature and underestimates the effect of precipitation. Further, we not only find differences in the size of the effect but also in significance levels. For example, when we use daily temperature and precipitation both affect total, violent, and property crime. However, when we use hourly data, temperature only significantly affect violent crime and precipitation has no significant effect on violent crime. Further, when we extend our analysis and consider a non-linear relationship between weather and crime, we again find relevant

[3] There also exists a related literature on hospital admissions and weather. For example, Rising et al. (2006) use hourly trauma admissions and hourly weather data over six years documenting a positive relationship.

differences between the two approaches. For both approaches, we find evidence for a non-linear relationship between weather variables and crime. However, using daily data we do not find a significant quadratic effect of temperature on violent crime, but significant effects of the other weather variables. In contrast, using hourly observations only temperature has a significant (linear and quadratic) effect on violent crime.

In conclusion, the frequency of the employed data has important and relevant implications for the size and the significance of the effect of a weather variable on crime. Further, the choice of the frequency also has implications for testing theories describing the weather-crime relationship. Therefore, the choice of the frequency of observations is crucial and leads to different conclusions about the relationship between weather and crime. This is important when one wants to derive suggestions for the allocation of police resources. Further, given that there is overwhelming evidence for increases in temperature and changing precipitation patterns (IPCC, 2012), our findings are relevant for the forecasting of criminal behavior (Ranson, 2014) used, for example, to allocate funding to law enforcement agencies and to develop policies and laws.

The paper is structured as follows. The next section reviews the theoretical contributions about the weather-crime relationship. Section 3 discusses our data and econometric strategy. Sections 4 to 6 then discuss our estimation results and extend the analysis by considering non-linear effects and lagged effects (or persistence of weather shocks). Section 7 briefly concludes and comments on limitations we face.

2 A Review of the Theory

Before we discuss our data set and our results, we want to provide an overview about how weather variables can affect human behavior and, therefore, crime. Clarke and Cornish (1985) argue that immediate events and conditions are key drivers of criminal behavior. This approach is crime-specific as they argue that the motivation and required behaviors vary across types of crime. Hence, this supports the idea that weather variables might have different effects on property and violent crimes.

We begin with theories that focus on the psychological impacts of weather conditions. These theories focus on the impact of weather on the individual. The *General Affect Model* proposes a linear, positive relationship between aggression and heat (Anderson et al., 1995). Temperature, in laboratory experiments, has been shown to affect behavior via affective aggression and arousal (Anderson et al., 1995 and Anderson and Bushman, 2002). In contrast, the *Negative Affect Escape Model* (Baron and Bell, 1975 and Bell, 1992) suggests an inverted U-shaped relationship between heat and aggression. Discomfort increases which results in an increase in aggression. However, there comes a point where the desire to escape the discomfort increases, decreasing the level of aggression.

An alternative to theses theories relying on psychological factors such as arousal and affect is the *Routine Activity Theory* (Cohn and Felson, 1979 and Cohn, 1990). It focuses on the event rather than the individual. This theory requires three elements for a crime to be committed, a suitable target, the motive to commit a crime, and the absence of a guardian to prevent the crime. It applies equally to property and violent crimes.

The theory suggests that our activities follow repeated patterns. Changes in the environment, however, do affect our behavior and these activities. On hot days, we might spend more time outdoors which increases opportunities for inter-personal contact and, therefore, increases the availability of victims. Similarly, it increases the number of empty houses and apartments, which makes them more vulnerable targets. However, it also increases the number of potential witnesses or guardians, which reduces the likelihood of a crime.

Finally, the *Excitation Transfer/Misattribution of Arousal Model* (Zillimann, 1983a, 1983b) states that the activation of the sympathetic nervous system resulting from excitatory reactions, is largely non-descriptive in terms of the emotion. As a result, a change in weather conditions resulting in a reaction in the sympathetic nervous system may be misattributed towards an individual in a similar manner.

A third model is the canonical model of crime (Becker, 1968), in which the decision on whether to commit a crime or not is based on a cost benefit analysis. The idea is that weather conditions are an input into a crime production function. Changes in weather conditions therefore impact on the probability of successfully committing a crime (Jacob et al., 2007 and Ranson, 2014) and, hence, actual behavior.

3 Data and Methodology

3.1 Variables

Crime data has been collected from the respective city's open data portals, with the exception of Indianapolis for which the data was collected from the Indianapolis and Marion County website. Data is provided by the New York Police Department, Chicago Police Department, Los Angeles Police Department and Indianapolis Metropolitan Police Department. The four cities are chosen based on their population size and the availability of data. Investigating both violent and property crime, it was important for crimes such as homicide and rape to be included. In several counties this information is not publicly available for confidentiality reasons. From each city, local time in minutes, the date, and nature of the crime (the penal code associated with the offence) is collected from the geocoded data set.[4] We expect that there is noise in reporting: some crimes might not be reported exactly at the time they are committed. However, as long as this delay in reporting is related to weather conditions, this will not affect our results. We observe data for 2014 to 2017. Overall, we have roughly 2.4 million observations. Crimes are categorized into violent crime (rape, homicide and assault and battery) and property crime (burglary, larceny, robbery and grand theft auto) following the finding by other papers in the literature (e.g. Jacob et al., 2006 and Horrocks and Menclova, 2011) that weather affects types of crime differently.

Combing the weather and crime data is done at the city-level. Weather data are collected from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information land-based stations. From these data, hourly recordings of temperature (dry bulb temperature, in degrees Celsius), the relative humidity (measured as a percentage), wind speed (measured in miles per hour), and precipitation (measured in inches) are collected.[5] Additionally, the local time and date of the reading are taken. Weather readings are rounded to the closest hour. Although recordings are mostly taken hourly, instances occur where multiple readings are taken within an hour. Subsequently, the average of the reading is taken to the nearest hour. Further, some readings are missing for particular stations. Subsequently, the weather reading is averaged across the stations for the particular city. This should not be a problem for our econometric approach unless the spatial effect between weather and crime would vary over time.

Descriptive statistics are presented in table 1. Overall, our sample contains roughly 2.4 mio. crime observations. This is broken up into about 790.000 violent and 1.6 mio. property crimes. Looking at the underlying characteristics reveals that within property crimes, 63 percent are larceny, 17 percent are burglary, while robbery and grand theft auto both make up 10 percent each. Within

[4] The data provided is for the "primary type" of the crime. We do not know whether, for example, a property crime also has a violent crime component.

[5] Notice that our measure precipitation cannot distinguish between rain and snow.

violent crimes, assault and battery make up 97 percent of total violent crimes. Rape and homicide make up 2 and 0.7 percent of violent crimes. There is little variation in these numbers across cities. The biggest differences occur for the composition of property crimes. Los Angeles has 30 percent burglary and 44 percent larceny compared to the other cities with predominantly larceny (Indianapolis: 57 percent, Chicago: 63 percent, New York: 77 percent). Further, rape in Indianapolis is about 9 percent, reducing assault and battery to 90 percent.

Over time, for all cities, we find that crimes occur more often during the summer months (June, July, and August). Interestingly, violent crimes across cities are highest between May and August, while property crimes peak slightly later. We find that most crimes, in all four cities, occur on a Friday (15 percent of crimes disaggregated by day of week). This holds mainly for property crimes, while violent crimes occur more often on a Saturday and Sunday. When we look at the highest frequency, we observe that crime peaks in the afternoon (around 6 pm). Property is high during the entire afternoon, while violent crime increases over the day and peaks between 8 pm and 10 pm. Interestingly, in Chicago violent crime peaks at 4 pm and then stays high until midnight, while in the other cities there is an almost linear increase in violent crime towards midnight.

Our study uses four weather variables. Average hourly temperature across city and time is 15.42 degree Celsius (59 degrees Fahrenheit) with an average humidity of about 58 percent. Wind speed on average is 16 kilometers per hour (10 miles per hour) and average precipitation is 12.45 mm (0.49 inches).

3.2 Econometric Approach

We choose a time series analysis using a general model

	Observations	Mean	Std. Dev.	Min	Max
Daily					
Total	2,385,324	282.10	123.61	1	644
Violent	784,999	180.57	55.33	2	500
Property	1,600,325	331.90	117.20	1	644
Hourly					
Total	2,385,324	60.90	35.70	1	221
Violent	784,999	37.97	16.82	1	115
Property	1,600,325	72.14	37.10	1	221
Temperature	2,383,181	15.43	10.01	-26.14	36.66
Humidity	2,385,238	58.42	18.95	0	100
Precipitation	2,360,190	0.49	0.90	0	22.20
Wind Speed	2,316,244	10.23	8.60	0	49

Table 1: Descriptive Statistics.

$$\log\left(Crime_{i,t}\right) = \alpha + \beta f\left(\mathbf{X}_{i,t}\right) + \eta_i + \eta_t + \varepsilon_{i,t}, \tag{1}$$

where cities are labeled i and t denotes time. We include a constant, α, and $\mathbf{X}_{i,t}$ contains our variables of interest: temperature, humidity, precipitation, and wind speed. We are interested in the size and sign of the parameters in β. The functional form, $f(\cdot)$, is assumed to be linear. However, since the range of the levels of our weather variables is sufficiently large, we also test for a non-linear relationship. For this purpose, we will also consider a quadratic form of f.

The model takes into account that cities exhibit a different average level of crimes and includes city fixed effects, η_i. Various time fixed effects, such as year, month, day, and hour, all captured by η_t, are included to capture other time-varying factors such as economic or demographic change. Finally, we also control for Federal holidays (Christmas, Independence Day, New Year's, Veterans Day, Martin Luther King Day, Memorial Day, Washington's Birthday, Labor Day, Thanksgiving, and Columbus Day) and the hour and day of full moon. Holidays might change behavior (e.g. time spend at home) and, therefore, could affect the number of crimes committed. Further, there might also exist a link between the lunar cycle and human behavior (Lieber, 1978). Finally, we use clustered standard errors at the city level for all regressions. The clustering problem is typically caused by a common unobserved random shock at the group level. This will cause all observations with in each group to be correlated.

We explicitly do not control for (socio-)economic variables such as income, unemployment, or education for three reasons. First, we are interested in the total (or direct) effect of weather variables on crime. Hence, controlling for other variables would change the interpretation to a partial effect. Second, these variables would not change much on a daily or hourly frequency and would, therefore, likely be absorbed by the fixed effects. Third, and most importantly, controlling for these variables would likely cause a bias in the β coefficients. This "bad control" problem, comes from the endogeneity of the control variables (Hsiang et al., 2013 and Burke et al., 2015): Income, for example, has been shown to be driven by climate variables (Dell et al., 2014).

Finally, a key advantage of our approach is that our explanatory variables are plausibly exogenous and we do not expect reverse causality to be a problem. While this reduced-form approach does not allow us to identify how our weather variables affect crime, causal inference is obtained by the random variations in weather variables within each city over time. This is further enhanced by the unprecedented high-frequency of weather and crime observations.

4 Main Results

To be able to compare our results to the related literature and to stress the differences from using hourly observations instead of daily observations, we run the same regression for daily and hourly crime across the types of crime: total, violent, and property. Our results are presented in table 2.

	Daily Total	Daily Violent	Daily Property	Hourly Total	Hourly Violent	Hourly Property
Temperature	0.007***	0.009***	0.006***	0.002	0.003**	0.002
	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.002)
Humidity	−0.0001	−0.001**	0.0002	0.0003*	−0.0002*	0.0005*
	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0002)
Precipitation	−0.03***	0.01**	−0.05***	−0.06**	0.02	−0.10*
	(0.004)	(0.002)	(0.007)	(0.01)	(0.04)	(0.03)
Wind Speed	0.00001	−0.0003	0.0002	0.0002	0.0005	0.0003
	(0.0005)	(0.0007)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Obs.	2,312,339	762,447	1,549,892	2,292,037	756,902	1,535,135
R^2_{adj}	0.95	0.93	0.93	0.82	0.71	0.83

Table 2: Main results. All regressions include city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are clustered at the city level and shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

We begin by discussing the results using *daily* data.[6] Total daily crime is significantly affected by temperature and rainfall. We find that higher temperatures have a positive effect on total crime. A one degree Celsius increase in temperature will increase total daily crimes by 0.7 percent (equal to two more crimes). Further, we find that higher precipitation will reduce daily crimes. The effect is about four times as large as the temperature effect. An increase in precipitation of one inch will reduce daily crime by 2.96 percent (equals 8.3 crimes). Finally, humidity and wind speed (as in Horrocks and Menclova, 2011) are always insignificant but for the effect of humidity on violent crime. Here, we find that higher humidity significantly reduces violent crime: a one percentage point increase in humidity (equal to 5.5 percentage points) will reduce daily violent crimes by 0.1 percent (equal to 0.2 violent crimes).

If we decompose total crime into violent and property crimes, we can understand what drives this results. The positive effect of temperature on daily total crime comes from both, violent and property crimes. For precipitation, we find that the negative effect comes from the large effect of precipitation on property crimes.

[6] In the following we will use the *level* of weather variables. The results are robust to using anomalies (observed temperature minus average annual temperature in our sample).

We find that violent crime reacts more strongly (by 50 percent) to temperature than property crimes. A one degree Celsius increase in temperature will lead to 1.6 more violent crimes (0.9 percent) and 2 more property crimes (0.6 percent). This positive effect is in line with the related literature and theories discussed earlier. This finding can be explained using the *General Affect Model* and the *Negative Affect Escape Model*. Higher temperature affects behavior via affective aggression and arousal and leads to more violent crime. A different theory that fits this finding is the *Routine Activity Theory* where behavior is affected by climatic factors and that applies to violent and property crimes. For example, on hot days people might spend more time outdoors increasing the availability of victims. Finally, the *Excitation Transfer/Misattribution of Arousal Model* also fits our findings where temperatures trigger a reaction in the sympathetic nervous system that can be misattributed towards an individual. The size of the temperature effect in our study is similar to the one found in Horrocks and Menclova (2011). They find an increase of about 1.5 violent crimes and about 1.2 property crimes using New Zealand data. The positive effect is also found in earlier studies such as Cohn and Rotton (1997, 2000), McDowall et al. (2012), and Ranson (2014).

Precipitation, interestingly, increases violent crime and reduces property crime. A one inch increase in precipitation will lead to 1.8 more violent crimes (1 percent) but reduces property crimes by 16.2 crimes (4.88 percent). The negative effect on property crimes can be explained using the *Routine Activity Theory* and Becker's (1968) theory of crime. Recall that the former requires three elements for a crime to be committed: a suitable target, the motive to commit a crime, and the absence of a guardian to prevent the crime. One could argue that precipitation will reduce the incentives for people to spend time outdoors. This would reduce the availability of suitable targets (empty houses, people in the streets) and, therefore, could reduce property crimes. However, with less people on the streets, this also reduces the number of guardians available, increasing the likelihood of committing a crime. Similarly, weather can be an input into the property crime production function. If higher precipitation reduces the likelihood of finding a suitable target, then this would reduce the probability of successfully committing a crime and, hence, the number of crimes committed.

The direction and size of the precipitation effect is different to the results obtained by Horrocks and Menclova (2011). They find that an increase in precipitation of 0.04 inches will reduce violent crimes by 2.6 percent. Similarly, they also find a different size and direction of the effect of precipitation on property crimes.

When we use *hourly* crimes, our results change dramatically. Total crimes are significantly driven by precipitation and humidity, albeit humidity is quantitatively unimportant. In contrast, when we used daily temperatures we found a highly significant (p-value < 0.01), positive effect of temperature as well. For violent crimes, we still obtain a significant effect of temperature. However, this effect is larger; roughly by a factor of two. For a one degree Celsius increase in temperature, we find an increase of 0.11 crimes per hour or 2.64 crimes per day, assuming that temperature is higher every hour over the entire day. Again, humidity is significant and has a negative effect on violent crimes. However, this effect is quantitatively unimportant. In contrast to using daily temperatures, precipitation has no significant effect on violent crime.

For property crimes, we find that the effect is much larger compared to the daily effect. We find that a one inch increase in hourly precipitation will reduce property crimes by 6.9 crimes per hour (164 per day). Humidity has a positive, significant effect which again is quantitatively unimportant. Interestingly, we find that temperature has no significant effect on property crimes.

Our results show that the literature using daily temperatures overestimates the effects of temperature and underestimates the effect of precipitation on crimes and leads to wrong conclusions about the significance of climate variables on total and types of crime. The conclusion from using hourly climate measures is that temperature affects violent crime, while precipitation affects property crimes. For daily temperatures, temperature and precipitation affected both variables.

Finally, we want to briefly discuss the effect of our control variables: holidays, day and hour of full moon. We find that holidays reduce total and property crimes but increase violent crimes. Cohn and Rotton (2000) find that holidays reduce the number of larceny-theft events. This finding is in line with implications of the *Routine Activity Theory* and Becker's (1968) theory of crime. Since holidays in this study are measured by public holidays that last only one day, one can argue that most people will stay home, which, similar to the effect of precipitation, reduces the availability of suitable targets. In addition, with more people on holidays the number of guardians increases and, therefore, reduces the probability of successfully committing a crime. On days with a full moon we find significantly more total crimes and more property crimes, whereas in the hour of the full moon we observe less violent crimes. This supports the idea that the lunar cycle can affect human behavior (Lieber, 1978).

5 Non-Linear Effects of Weather

In the previous section, we have provided evidence that weather variables (mainly temperature and precipitation) have an effect on crime. Further, we documented that the measurement of the weather-crime relation is sensitive to the unit of observation. In this section, we want to extend our analysis and consider potential non-linearity in the weather-crime relationship. For example, the *Negative Effect Model* (Baron and Bell, 1975 and Bell, 1992) suggests that the temperature-crime relationship is inverted U-shaped with a turning point. Temperature increase to the left of this turning point will increase crime albeit with marginal decreasing returns. However, discomfort increases up to a point when individuals want to avoid this discomfort and try to escape it. This, in turn, will reduce the level of aggression and crime. As in the previous section, we compare the

	Daily Total	Daily Violent	Daily Property	Hourly Total	Hourly Violent	Hourly Property
Temperature	0.009^{***}	0.01^{***}	0.008^{***}	0.005^{**}	0.007^{***}	0.004^{**}
	(0.001)	(0.001)	(0.001)	(0.0009)	(0.001)	(0.001)
Humidity	0.0006^{*}	0.001^{*}	0.0003	-0.0008^{*}	0.001	-0.002
	(0.0003)	(0.0005)	(0.0004)	(0.0003)	(0.001)	(0.001)
Precipitation	-0.03^{**}	0.03^{**}	-0.05^{**}	-0.06^{**}	0.06	-0.12^{*}
	(0.007)	(0.008)	(0.01)	(0.02)	(0.05)	(0.04)
Wind Speed	-0.002^{*}	-0.003^{*}	-0.001	-0.003^{*}	0.00004	-0.004^{***}
	(0.0007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0007)
Temperature^2	-0.0001^{*}	-0.0001	-0.0001^{**}	-0.0002^{***}	-0.0002^{***}	-0.0001^{**}
	(0.00003)	(0.00004)	(0.00003)	(0.00003)	(0.00002)	(0.00003)
Humidity^2	$-7.9e^{-6*}$	-0.00002^{**}	$-2.6e^{-6}$	$7.3e^{-6*}$	-0.00002	0.00002^{*}
	$(2.6e^{-6})$	$(4.8e^{-6})$	$(3e^{-6})$	$(2.9e^{-6})$	(0.00001)	$(7e^{-6})$
Precipitation^2	0.002^{**}	-0.001^{***}	0.003^{**}	0.003^{**}	-0.003	0.006^{*}
	(0.0005)	(0.0002)	(0.001)	(0.001)	(0.003)	(0.002)
Wind Speed^2	0.0001^{**}	0.0001^{**}	0.00005^{**}	0.0001^{*}	0.00001	0.0001^{**}
	(0.00001)	(0.00002)	(0.00001)	(0.00004)	(0.00003)	(0.00003)
Obs.	2,312,246	762,447	1,549,892	2,292,037	756,902	1,535,135
R^2_{adj}	0.95	0.93	0.93	0.82	0.72	0.83

Table 3: Non-linear Effects. All regressions include city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are clustered at the city level and shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

outcome using daily and hourly observations. Table 3 presents our results.

We begin by discussing the results using *daily* observations. We find an inverted U-shaped pattern for the impact of temperature and humidity on total crime. However, as before, the effect of humidity is quantitatively not important. This finding is in line with the evidence provided by Cohn and Rotton (1997) who also find a positive linear effect and a negative quadratic effect of temperature on crime. The turning point for temperature is found to be at 45 degrees Celsius, which is outside the observed temperature range. Further, we find a U-shaped effect of precipitation and wind speed on crime. This implies that, relatively speaking, more crimes are committed when there is almost no precipitation and at high levels of precipitation. The turning point is found to be at 15 inches of precipitation. The turning point for wind speed is at 15 kph, but the effect on crime is quantitatively unimportant.

For violent crime, we only find a positive linear relationship between temperature and crime, which supports the *General Affect Model* and contradicts the *Negative Affect Escape Model*. Humidity, again, shows an inverted U-shaped relationship. Precipitation, interestingly, also has an inverted U-shaped effect on violent crime. Wind speed has a U-shaped effect on violent crime. The non-linear impact of weather variables on property crime is slightly different. We find an inverted U-shaped pattern in temperature while there is a U-shaped pattern in precipitation and wind speed. Humidity has no significant effect on property crimes in our sample.

In conclusion, when using daily observations, we find support for the *General Affect Model*, because there is no significant quadratic effect of temperature on violent crime. The non-linearity of total crimes in temperature is generated by property crimes (where the *General Affect Model* or the *Negative Affect Escape Model* do not apply). The non-linearity in property crimes can be explained by the *Routine Activity Theory*: when temperature increases, people might spend more times outside increasing the probability of finding a victim and increasing the number of empty houses. However, when temperatures become too high, people might avoid spending time outdoors, which reduces the probability of finding a victim and reducing the number of empty houses. For precipitation, we find that total and property crimes have a U-shaped pattern in precipitation and violent crimes have an inverted U-shaped pattern. For violent crime, the explanation could be that once precipitation crosses a threshold (15 inches) people will rather stay home and, therefore, are not available as victims or perpetrators. For property crimes, we can think about the absence of a guardian as a potential explanation for the U-shaped pattern. If more precipitation reduces the number of people outdoors, this reduces the number of victims and the number of guardians. This could lead to the observed result.

When we run the regressions using *hourly* observations, we find important differences. In contrast to using daily data, we find that temperature has an inverted U-shaped pattern for violent crime and that precipitation has no significant effect on violent crimes (neither linear nor quadratic).[7] The former finding supports the *Negative Affect Escape Model* over the *General Affect Model*. This theory (Baron and Bell, 1975 and Bell, 1992) predicts and inverted U-shaped relationship because at some temperature level the desire to escape the thermal discomfort increases, which decreases the level of aggression and hence, reduces crime. This finding is in line with Cohn and Rotton (1997) who document non-linearity for the relationship between temperature and assault. Further, Rotton (2014) shows that the number of monthly crime (robbery, larceny, and burglary) is affected by the daily maximum temperature in a non-linear way. Using hourly data, we find the following turning points: 12.5 degrees Celsius for total crime, 17.5 degrees Celsius for violent crime, and 20 degrees Celsius for property crime. These turning points are much more plausible than the 45 degrees Celsius turning point obtained using daily data. Recall that mean temperature is 15.43 degrees Celsius in our sample. Horrocks and Menclova (2011) find a quadratic form (inverted U-shaped pattern) for violent and property crimes in New Zealand. They show that violent crime peaks around 25 degrees Celsius, while property crimes peak around 20 degrees Celsius.

Moreover, temperature appears to be the only driver of violent crime when we use hourly observations. Property crime, in contrast and in line with the *Routine Activity Theory*, is affected by temperature, precipitation, and (although quantitatively unimportant) wind speed and humidity. The precipitation turning point is calculated at 10 inches.

Overall, this section has two main results. First, we find evidence for a non-linear relationship between weather variables and crime. Second, we again show that the results are sensitive to whether we are using daily or hourly observations. This holds particularly true for violent crime. Using daily data, we do not find a significant quadratic effect of temperature but significant effects

[7] Additionally, the absolute and the squared deviation of temperature from its annual average both have a negative effect on violent crime, which also supports this obtained non-linearity.

of the other weather variables. In contrast, using hourly observations only temperature is significant. This also has implications for testing theories of the weather-crime relationship. While the daily observations support the *General Affect Model*, the hourly observations support the *Negative Affect Escape Model*. Therefore, the choice of the frequency of observations is crucial.

6 Lags of Weather

So far, we have assumed that crime and behavior is only affect by current weather conditions, i.e. the current level of temperature, precipitation, humidity, and wind speed. In this section, we want to investigate whether weather shocks "build up" and have persistent effects on criminal behavior. For example, temperature and humidity during night time could affect sleeping patterns that could have an effect on the day (Okamoto-Mizuno and Mizuno, 2012). For this purpose, we consider various lags of *hourly* weather variables. To be precise, we use the following lags: weather conditions 1, 2, 3, 6, 12, 24 hours ago. Table 4 presents our estimation results.

For total crime, we find that the temperature in the previous hour has a negative effect on crime but that the temperature 12 hours ago has a positive effect on crime. Since crime (violent and property) peak between 2 pm and 10 pm (implying that temperature during 2 am to 10 am matters), this would support the idea that temperature affects sleep (Okamoto-Mizuno and Mizuno, 2012) and, therefore, criminal behavior (Meldrum et al., 2013). This effect is generated by property crimes. Precipitation has an interesting lag structure as well. Precipitation also has an interesting lag structure. Precipitation 1, 6, 12, and 24 hours ago have a (negative) effect on total crime. For property crime, the one hour and the 24 hour lag have a negative effect, while the 6 hour lag has a positive effect on crime.

Overall, past weather shocks have a persistent effect on crime.

Variables	Total	Violent	Property	Variables (cont'd)	Total	Violent	Property
Temperature	0.006 (0.003)	$-5e^{-6}$ (0.004)	0.007* (0.003)	Precipitation (-1)	−0.02** (0.007)	−0.002 (0.01)	−0.03** (0.01)
Humidity	0.0004* (0.0001)	−0.0001 (0.0002)	0.0006 (0.0004)	Precipitation (-2)	−0.009 (0.01)	−0.02 (0.01)	−0.007 (0.01)
Precipitation	−0.03* (0.01)	0.03 (0.03)	−0.06** (0.01)	Precipitation (-3)	0.003 (0.01)	−0.03 (0.02)	0.02 (0.01)
Wind Speed	−0.001*** (0.00004)	−0.0004 (0.0003)	−0.001** (0.0001)	Precipitation (-6)	0.08** (0.02)	0.03 (0.02)	0.11** (0.03)
				Precipitation (-12)	−0.06* (0.02)	−0.05 (0.02)	−0.05 (0.03)
Temperature (-1)	−0.004** (0.001)	−0.001 (0.002)	−0.004** (0.0001)	Precipitation (-24)	−0.03*** (0.004)	0.02 (0.03)	−0.05** (0.01)
Temperature (-2)	0.001 (0.001)	0.003 (0.004)	0.0004 (0.001)	Wind (-1)	−0.0002 (0.0002)	−0.0002** (0.0001)	−0.0001 (0.0003)
Temperature (-3)	−0.003 (0.003)	−0.002 (0.004)	−0.002 (0.002)	Wind (-2)	0.0003 (0.0003)	0.0002* (0.0001)	0.0003 (0.0004)
Temperature (-6)	−0.0002 (0.002)	0.002 (0.002)	−0.001 (0.003)	Wind (-3)	0.0003 (0.0003)	0.0007** (0.0002)	0.0003 (0.0004)
Temperature (-12)	0.005** (0.001)	0.001 (0.002)	0.01* (0.002)	Wind (-6)	0.0006 (0.0004)	0.0008** (0.0002)	0.0007 (0.0004)
Temperature (-24)	−0.001 (0.001)	−0.0001 (0.001)	−0.001 (0.001)	Wind (-12)	−0.001** (0.0002)	−0.002** (0.0005)	−0.001 (0.0003)
Humidity (-1)	0.0001 (0.0001)	0.00005 (0.0003)	0.0001 (0.0002)	Wind (-24)	0.0001 (0.0002)	0.0008 (0.0005)	0.0001 (0.0003)
Humidity (-2)	0.0002 (0.0002)	0.0004 (0.0004)	0.0003* (0.0001)				
Humidity (-3)	−0.0003 (0.0003)	−0.0007 (0.0004)	−0.0003 (0.0004)				
Humidity (-6)	−0.0002 (0.0004)	0.0001 (0.0004)	−0.0004 (0.0004)				
Humidity (-12)	−0.0006 (0.0005)	−0.0003 (0.0004)	−0.001 (0.0005)				
Humidity (-24)	0.0003* (0.0001)	−0.0001 (0.0001)	0.0005*** (0.0001)				
				Obs.	1,963,644	653,747	1,309,897
				R^2_{adj}	0.82	0.72	0.82

Table 4: Lags for hourly crime. All regressions include city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are clustered at the city level and shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

7 Conclusion

In this paper, we study the weather-crime relationship using a unique high-frequency, city-level data set. The key difference to the existing literature lies in matching *hourly* crimes to *hourly* weather measures. This improves the identification of the effects of weather on crime and increase the number of observations and, therefore, the variation used in the estimation.

We construct a crime data set at the city level (Chicago, Indianapolis, Los Angeles, and New York) between 2014 and 2017. Overall, we use more than 2 million observations in our analysis. We combine the crime data with weather data from weather stations. The four weather variables studied are temperature, humidity, precipitation, and wind speed. Further, we categorize crime into violent crime (assault and battery, rape, and homicide) and property crime (larceny, robbery, burglary, and grand theft auto) and study the effect of weather variables on these types of crimes. Finally, we investigate non-linear effects of weather and the persistence of the effect of weather conditions on crime.

We find important differences between using hourly observations and daily observations. The literature using daily observations overestimates the effect of temperature and underestimates the effect of precipitation. Moreover, we also find differences in significance levels across the two approaches. The most important difference is found for violent crime: when we use daily temperature and precipitation both affect total, violent, and property crime. However, when we use hourly data, temperature only significantly affect violent crime and precipitation has no significant effect on violent crime. We then consider potential non-linearity in the weather-crime relationship, we again find relevant differences between the two approaches. When we use daily data we do not find a significant quadratic effect of temperature on violent crime, but significant effects of the other weather variables. In contrast, using hourly observations only temperature has a significant (linear and quadratic) effect on violent crime.

In conclusion, the frequency of the employed data to study the effect of weather and crime has important and relevant implications for the results. A low frequency of observations can lead to different conclusions about the relationship between weather and crime. This is important when one wants to make recommendations for the allocation of police resources.

Finally, we want to discuss the limitations our study faces and the future research agenda. One shortcoming of our analysis is that we cannot account for potential endogeneity of police behavior. If police anticipates that higher temperatures lead to more crimes they might allocate more resources on hot days. This could lead to more crimes being reported in our data set simply because more police officers are on duty. We can not control for this potential endogeneity and also have not been able to obtain information from Police Departments about resource allocations. Next, we have not used the spatial information contained in our data set. We are assuming that each city is comparable with itself over time. While we investigated the data and have not seen large shifts in the spatial dimension of crime, this still might be a potential issue in the estimation. Especially the error terms might suffer from spatial correlation. Finally, to avoid bad control problems we have not included any control variables. We plan to address the last two issues in a spatial regression model combined with Census data in the future. However, this approach relies on an appropriate identification strategy.

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