Estimating The Weather And The Crime Rate

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Abstract

This paper sets to find out the correlation between the crime rate and the weather from an economic point of view. Many papers have working on this issue (REF Climate), but most of them focus on temperature only rather than other factors. By raising questions, there are more factors involved in this topic. Omitting variables could be precipitation, snow, wind speed, and 'snow on the ground'. As the list keeps going on, this paper will focus more on these factors.

Introduction

Climate change is a controversial topic nowadays, and this may affect the government's economic decisions. There may be more and more extreme weather, as meteorologists predicted will affects not only the temperature but also the other weather measurement variables. NASA (2019) Cho et al. (2019) As we acknowledge, humans are emotional lives—that explains peoples' action is hardly predictable. Even though thousands of economists came up with neat and considerable models, sometimes, it is impossible to practice in the actual world. For instance, the prisoner's dilemma, one of the most famous theory, fails almost 50% in reality since more than 50% of inmates fully cooperate instead of betraying each other as the theory predict. Khadjavi and Lange (2013)

If people dropped the assumption of rationality, there would be lots of uncertainty kick in, such as human emotion what is nearly unrealizable to be measured. However, the weather can be measure by precipitation, snow, wind speed, and 'snow on the ground' and the one-day maximum temperature. Numerous research suggests weather plays a vital role in emotion. Thus, it builds a bridge between the weather and the crime rate. Denissen et al. (2008)

If we know more about how weather affects crime or emotion, such additional relationship may help to access the correlation between human behaviour and crime. From a microeconomics point of view, such effect proves the weather may introduce more crime. In general, suppose the government agent learn about this pattern, the government reallocated resources wisely to prevent such a social problem and can also carry out how climate change affects the human being. After all, climate change beyond our expectations.

The weather has two sorts of effects on crime. For instance, a snowy day may let criminals less likely a crime when snow on the road, such is a direct effect. The indirect effect will be weather affect emotion, which affects the number of crimes. In this paper, we are focusing on the total effect, which combines both effects. In addition, the direct effect will be less likely to be measured, especially for the wind speed and the temperature. The core idea is how the weather affects crimes. After this research, the result can tell us which weather variable affects crime mostly and helps us to predict the crime rate due to weather forecast.

Literature Review

Through several past works of literature, they imply a causality correlation between the crime and the weather but put more weight on the violent crims and the temperature. However, the weather has less regressional usage as a variable since it is a vague, abstract word. In order to solve this problem, this paper utilizes more weather variables, and most of them are not having an instrumental variable to specifically defined the weather variable. However, we will try to overcome this by measuring the total effect and corporate multiple—control variables to reduce bias and increase consistency.

Past dataset usually captures an extended period, Blakeslee and Fishman (2014)most of the works are employed a longer monthly period in how income affects the crime rate since the weather is an essential factor for agricultural income. Income is excluded in our regression since our primary goal is the short-run emotional effect on a day-to-day basis

Even if panel data is using daily data, most of them are not focus on how weather affects crime. One of past research put it in the regression but does not put more weight of the paper on it because the goal of that paper is exploring the correlation between sport events and family violence. Card and Dahl (2011) Although it shows that temperature will significantly affect the crime rate, they didn't discuss why it would be the case. The paper here will focus on discussing the weather.

The paper you are reading will discuss how weather affects a different type of crime and how each type of response. The result should show how different crimes react to weather, which may suggest the difference in the astute of different crimes. Which is different from other research usually left the data of crime type behind. They usually come together in the dataset.

The temperature used to predict the crime rate may be the result of how the data is easy to collect and the relative completeness. Temperature data are most commonly available over the years. From my research site, the temperature data can go as far as 1966. The long duration gives better data—in recent years. The observation sensor for the weather goes up and improves the quality of the data since we have more massive weather data set, and more weather variables can be used as research. For example, snow on the ground is a newer variable that was not expected. In the data set, the missing the data in our data set was minimal and even better than some other variable that expected

to be complete. So, it was included in our paper. 1

Data

The variable require will be weather and crime; the weather data set included every functioning weather sensor in Chicago. However, most of them only work for a couple of years and measuring some but not all-weather variables. They measure all kinds of weather variables daily which include wind direction, and soil temperature. Most of them were dropped due to their incompleteness. The crime dataset comes from the Chicago government contain every crime committed in Chicago that has been reported. The type of crime, place and time are all recorded in the dataset, which gave us the fundamentals to work with, so we can explore how weather affects the different type of crime.

The data are collected from the dataset are transform into the way required. The sensors over Chicago may only monitor one or two variables on a daily bias. There was no complete data in one sensor, and representative data over the city is needed. The average of all available sensors was token and mark as the average weather variable. To do so, we maximize the coverage, which provides a complete dataset with almost no missing spot. The sensor is spread all over the city, which also provides representative data. There were lots of other variables left out due to incompleteness, such as sunlight. They can be used in further research since the quality and quantity of them increases. The precipitation is measure by daily rainfall in inch. The maximum temperature will be measure in the Fahrenheit. Wind speed will be measure as the miles per hour as a daily average. The snowfall will be measure in inches as the depth. Then, a daily average is calculated for all the available sensors and a almost complete data set were created. One extra variable was calculated which is water equivalent snow on the ground. It isn't including our later discussion due to there are around 50 day missing for water equivalent snow on the ground and it is similar to other variable (snow on the ground). the maximum temperature has the highest standard deviation follow by wind speed. The rest of them have a lower standard deviation, which will affect economic significance.

2

For the crime rate, they are calculated based on counting how much crime reported each day. Since our data only has the crime number reported, it does not count if the police decide to investigate themselves. - There will be different types of crime. Total crime will be used as well as all type of crime since most of the past research focuses on violent crime due to the main target of them is

the study's emotional aspect. There is no proof that other crimes cannot be driven by weather so that we will be classified crime as a whole, and we also study other crimes. Then we break down into a couple of different segments, which are violent crime, deceptive practice(lie), theft, drug, sex, children related, human trafficking and gambling. These are the main type show in the data with some crime merge together into a more significant type the similar in behaviour. Violent will arson, battery, criminal damage, assault, robbery, criminal trespass, weapon violation, public Pease violation, sexual assault, sex offence, interference with a public officer, homicide and kidnapping. Theft will include motor vehicle theft and burglary. Sex will include prostitution, sexual assault and sex offence. At this point, we ignore is that the suspect gets arrested or not. Some of them are left out as other crime due to the fact they take less than 1% of the value, and most of them are not suitable to classified into any category mention above. Their absence should not affect our results. 3

The Empirical Problem

Using time-series data to identify how weather affects the crime rate, The data come from the Chicago Data Portal and Global Historical Climatology Network. Chicago was chosen because it has one of the best datasets. The dataset contains the time, type and place for each crime reported to the police officer. Then a daily average was calculated for each day and serve as an endogenous variable. The weather data contain wind speed, precipitation, snow and snow on the road as a daily average. The maximum and minimum temperature per day are also included. Then are collected from over 300 weather sensors located in Chicago. Unfortunately, none of them contain comprehensive data, and some of them shut down or close after a period of use, so the data we use will be the average of all available sensors. Since Chicago is treated as a whole, and only the data with the highest coverage level were used, the data we get should represent Chicago.

Only Chicago data were used due to more natural control, and none of the data has such richness. Also, change in GDP or other change should happen rather slowly. Including such a control variable will not help much because they are changing slowly, and those variables are not likely to be daily data. The police spending on that year is relatively stable (gov spending), and the population did not change much from 2011 to 2017(American fact finder). These let the assumption that the background remains unchanged over the years other than the stuff will be talking about later on. For the past 20 years, there is only one significant change in the police department, and the justice system Department (2020)introduces some programs to lower crime rates starting in 2004. So from January 1st, all observation will have a dummy variable equal to one indicate such effect. The dataset using is based on daily levels, and daily data raises the concern that each day are not having a similar background of crime. There will be holidays that affect the crime rate due to more human interaction. Jett et al. (2018)The solution will be adding all federal holiday is added with a dummy variable to account for the effect.

There will be an assumption that needs to be made. They are necessary for our paper. Without it, there will be no way to proceed as an economics student. The fraction of crime records each day will assume to be the same. There will be no way we can find out how many crimes happen. Crime is something most people want to hide. A crime done with care and luck may escape. There will be

no instrumental variable to solve escaping problem. The only way is assuming the fraction of crime is constant.

The demographic and population characteristic are assumed to be the same over the years. Although there will be no way to be the same over the years, they are relatively similar or moving at a relatively steady pace. The effect of those stable variables, the effect on our result, is minimal. Those moving at a steady pace, such as real GDP, have a steady growth rate over the years. Even if it causes bias on our regression model, the bias would be on the constant term estimator. The weather itself should be unbiased.

There will be one type of crime that would be treated differently. The type will be the combination of concealed carry violation and alcohol violation. The difference between them is base on the nature of concealed carry and alcohol crime. The law about them is prohibited firearm to enter certain places or to sell alcohol in a prohibited time frame. ChicagoChicago (2010) The idea is, the owner of the alcohol store will always violate the law if they decided to do so, and the number of them get reported will serve as an indicator of police service. Since we assume every day, there will be the same amount of people doing the same crime. The number of them getting caught may suggest the weather may change the quality of the crime report. There may be a better reporting system someday. So, it will be included in all regression we will perform later as an indicator of quality in the research system and will control the effect of the research system. Since we are only interested in how weather affects actual crime, not how the reporting system work under different weather.

4

We use the underline formula:

$$CrimeRate = P0 + P1Precipitation + P2WindSpeed + P3Snow + P4snowontheground + P5MaximumTemperature + P6Holiday + P7Date + P8Date^2 + Error$$

The relationship will be solved by the time-series approach. As previous suggests, our paper

will focus on the total effect.

dCrimeRate/dWeather = dCrimeRate/dPathway + dPathway/dWeather

The pathway variable can take on anything but the weather variables. The focus is on P1-P5. Others are control variables. The crime rate will represent total crime and different kinds of crime individually so we can study which type of crime will affect the most by the weather and which type of weather. Since we are using a time series method, we need to derive the relation step by step. All of the variables we are using except control variables.

The unit root test needs to be performed to check if all variable is stationary. After performing duck fuller test on all of them, it is fortunate that all variable has a low p-value so the null hypothesis that any of them have unit root can be rejected. All of them are stationary. Then, we can directly estimate their relationship by performing the newey standard error regression with the lag calculated to be 10.

The regression can be run in many different ways. Our concern is the total weather effect on a different type of crime, which is performed as follows.

5

The regression of total crime suggests all-weather variables. We have a significant effect on the crime rate. Wind, rain, snow and snow on the ground are negatively correlated to the crime rate, and the maximum temperature of the day will positionally correlate. There is also a trend on the crime rate, which may cause by technology or something else, which is fine. The inclusion of time and square of time should capture such effect well enough. The problem now is economically significant; the average crime per day is around 1000. Rain, snow and snow of the road are relatively insignificant because their variation is small. They are relatively difficult to affect the crime rate on a large scale unless extreme weather. Temperature and wind speed are because they have high variation. However, all of them will not affect the crime rate a lot due to their coefficients are not large, but at the same time, not something we can ignore. Although increase a couple more crime is not major in an economic point of view since it will not impact the economic variables much.,

crime is something that cannot easily measure. Crime is affecting at least one person's future. So though out the paper, if weather variable can easily fluctuate the number of times more than a couple of percent. They will be considered economically significant. Also, we are considering a Fest on all-weather variables to see their total significance.

Then, we are going to consider the effect of weather in a different type of crime, since crime is different, some crime is more emotional and limited by the environment variable. Some of the crimes did not.

6

There are roughly similar to the total crime we calculate before. All of them are statistically significant. Wind, rain, snow and snow on the ground are negatively correlated to the crime rate, and the maximum temperature of the day will positionally correlate. A similar trend is also observed. It is more economically significant than statistic significance. The average violent crime per day is roughly 500, which is half of the total crime. Then we compare the coefficient to the regression of total crime. Rain and the maximum temperature do not change much compared to the coefficient from above. They are relatively economically significant compare to the total due to every unit change in them will have more percentage change on violent crime than total crime. They are relatively significant. Another coefficient is roughly half of the total crime. Those coefficients conclude that violent crime is relatively more sensitive to weather relative to total crime.

7

For the effect of the crime of deceptive behaviour, the significant level is much smaller. Except for maximum temperature and wind, none of them are significant. The weather has less effect on deceptive behavior type of crime, and the significant level is also lower on maximum temperature and wind speed from a statistic point of view. Also, by the F test, the P value is much high then most of other crime. From an economic point of view, the thing goes a little bit differently. Keep in mind that around 40 of deceptive behavior kind of crime happens every day. Deceptive behavior is way less compared to total or violent crime. So, a lower coefficient is understandable compare to total crime due to the fact that they happen less than we predict. Still, the snow has an effect that too small to cause any significant changes similar to others. The effect on them is too small to cause

any changes. They are economically insignificant, and the result is something we expected due to deceptive behavior require less face to face interaction due to improvement in technology, so traffic is not a problem.

8

For theft, the coefficient is statistically significant for wind speed, snow, snow on the ground and maximum temperature. The coefficient on rainfall is not significant. The result is expected and shows that weather has less effect on crime compare to total crime. Also, for economically significant, there will be roughly around 300 daily theft crimes. In general, most of them are insignificant because they will not affect theft much. Except weather temperature is still significant due to the deviation of it is high, and it can affect theft on a larger scale. In general, none of them are as significant as the weather on total crime may suggest theft are less responsive to weather.

Also, an interesting factor in the control variable. The date is statistically insignificant. The result suggests there may not be a trend in total crime and suggests that total crime is not time sensitive. It does not change over time, which raises a question that will be discussed afterword.

9

For drug consumption, the result of different as any other crime we discuss before. Temperature is usually something statistically significant. It is different for drug. Snow on the road is also insignificant. The rain, wind speed and snow are significant for drug. For economic significance, none of them seems significant with the average of 100 of drug every day. Something in the control variable raises a question. The change in 2004 should be reducing crime. The result here disagrees. The drug consumption gets reported rise after the effect. Such result may cause by a better policing system increase reporting efficiency. The coefficient reflects the quality of reporting system may increase number of crimes reported. Although such unexpected event occurs, we still capture such effect.

10

For sex relative crime, we can see that most of the weather variables are not significant. Snow on the ground, wind speed and rain are not significant, but the F test suggests in general, they are still significant. Weather still affects related crime statistically significantly, from an economic point

of view, all of the significant factors due to the sex-related crime itself happens relatively rare. On average less than 20, causing weather variables with a smaller coefficient can still easily affect how many sex crimes happen every day.

11

All of the variables that except snow on the ground are both economic and statistically significant. The result suggests there may be a large correlation between gambling and weather. The customer of gamble or gamble facility itself may be heavily related to weather which makes economic sence since gambling is always violating economic theory. The expected profit is always lower than the cost. The reason being those people are risk loving. These kinds of people most likely consider irrational; they may be heavily affected by the weather.

12

For human traffic, Only snowing is statistically significant. Others are insignificant. The F test fail to reject the null hypothesis that they are insignificant, but the P-value is much higher compared to most of other crimes. Also, the coefficient is so small that they are all economically insignificant. In general, human trafficking is less affected by the weather. A hypothesis on such result is due to human trafficking is a serious and time-consuming crime. It requires a lot of planning and preparation. So, in general, it is less affected by emotion or environment variable due to the input of sunk cost.

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Children relative crime is not statically insignificant in snow relative weather and significant in rest of them. The economic significant suggest similar result. There are around 7 children relative crime happen daily. So, a smaller coefficient can be still influential on most of them except snow relative factor.

Conclusion

In summary, the result is both expected and surprising. The result on rainfall, snowfall, snow on the ground and temperature are expected. The first three of them cause trouble with traffic, which may affect human interaction. The hypothesis is similar to past research by Gary Becker. Becker (1968) The simple explanation will be crime base on the valuation on cost and benefit. Our paper is based on the research on the city, so we do not need to care about agricultural income may be affected. The production in the city is more indoor and is less likely affected by the weather. The weather may affect the crime rate of success and difficulty to escape Jacob et al. (2004), which is consistent with our results, especially violent crime.

Also, due to the fact that crime is the most likely interaction between humans in daily life Glaeser et al. (1995) which is also consistent with our results. It has proved to be profoundly affected by the weather.

Some of them are not what we expected. The biggest one, wind speed. The coefficient and significant level are way larger than expected. There is less paper discussing such an effect, which is significant in our research which discloses one of the drawbacks of our research.

We do not know how each weather factor affects crime. The result will surely tell us how each weather factor affects the crime rate, but how? The result cannot answer such question because we can only consider the total effect. For example, the weather will affect GDP Kahn et al. (2019) ,and GDP affect crime due it change labour income. There will be an indirect effect. our research cannot tell how they interact with each other and give us the final result. If more daily control variables are given and more volatile. The additional variable may help answer the questions.

Also, when studying crime. It would be better to have more data by using a panel data approach. There is a limit base on technology problems and time constraints. The combined data set is extensive that a personal laptop is not the right choice of running it and analyzing other cities and transform them into useful data would be too time-consuming.

There is a technology problem in the data itself. The data are used from 2001 to now. The temperature sensor in 2001 is less technology advance and only 30 of them in the city for comparison. There will be at least 100 sensors working every day in the city. Some of the data that have not

been considering affecting crime before are missing. Some of the most basic such as average daily weather is missing for a couple of years. These let the weather left chosen limited. Over time these problems may resolve as the increase in data.

Some of the regression show that numbers of weather sensors have a significant effect on crime may also mean the crime rate will be effect by the number of the sensor and seems impossible. The uncertainty may be raised from the difference in sensor number that may change measurement quality. Luckily, for further research, maybe use only a couple of sensors for there are fixed and use for an extended period of time. Sadly, such a data set is not existing yet because most data sensors will be replaced after a couple of years of usage due to hardware problems. In my data set, most of the sensor does not survive for more than one year.

Although our research is not perfect, the result is significant. Some of them are what we expected due to similar research in the past, and this our research confirms their result. Also, it raises some new questions worth further research. The effect of crime on the weather is definitely there. The temperature will rise crime rate, wind speed, rainfall, snow, and snow on the ground will decrease the crime rate. Temperature and windspeed are less likely to affect the background of the crime. The only thing they are easier to affect is human emotion. The result of our paper proves is that human emotion plays a part in the crime. The temperature increase due to global warming might also affect crime in the long run which increases the drawback of global warming.

Appendix



Figure 1: U.S. recession

Variable	Obs	Mean	Std.Dev.	Min	Max
violent_c	6979	417.997	119.776	123	836
theft_c	6979	318.251	82.853	101	661
sex_c	6979	81.012	28.397	23	278
lie_c	6979	41.179	14.776	5	213
game_c	6979	2.088	2.38	0	16
drug_c	6979	104.471	50.668	3	559
ht_c	6979	.009	.098	0	2
chrildren_c	6979	7.112	3.848	0	47
contral_c	6979	2.131	2.042	0	14
other_c	6979	1013.108	263.943	320	2027
argand	6989	9.067	3.477	1.713	26.693
avgprcp	6989	.113	.26	0	3.762
avgwesd	6975	.071	.313	0	12.05
avgtmax	6989	59.755	20.796	-2.5	102.111
avgsnow	6989	.093	.511	0	14.879
avgsnwd	6989	.575	1.826	0	18.225
OBS	6989	73.859	43.718	0	212

Figure 2: Summary

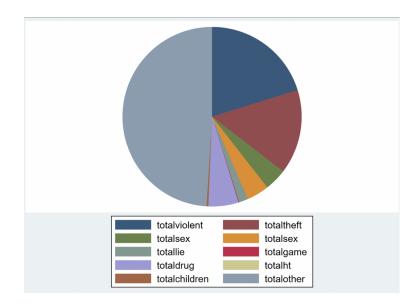


Figure 3: Summary Distributions

contral_c	Coef.	St.Err.	t-	p-	[95%	Interval]	
			value	value	Conf		Sig
avgawnd	-0.015	0.006	-2.39	0.017	-0.028	-0.003	**
avgprcp	-0.228	0.072	-3.18	0.001	-0.369	-0.087	***
avgtmax	0.011	0.002	6.93	0.000	0.008	0.014	***
avgsnow	0.026	0.039	0.67	0.504	-0.050	0.102	
avgsnwd	-0.033	0.012	-2.76	0.006	-0.056	-0.010	***
edate	0.000	0.000	-	0.000	0.000	0.000	***
			17.62				
holiday	-0.675	0.111	-6.07	0.000	-0.894	-0.457	***
OBS	-0.003	0.001	-2.68	0.007	-0.005	-0.001	***
change	-0.589	0.115	-5.13	0.000	-0.814	-0.364	***
Constant	9.795	0.390	25.14	0.000	9.031	10.559	***
*** p<0.01, *	** p<0.05, * p	p<0.1					
*** p<0.01, 3		o<0.1					
(1) avgawn (2) avgprcp	d = 0 $0 = 0$	><0.1					
(1) avgawn	d = 0 $0 = 0$	o<0.1					
(1) avgawn (2) avgprcp	d = 0 $0 = 0$ $0 = 0$ $0 = 0$	o<0.1					
(1) avgawn (2) avgprer (3) avgtma	d = 0 $0 = 0$ $0 = 0$ $0 = 0$ $0 = 0$ $0 = 0$	><0.1					
 avgawn avgprer avgtma avgsnov avgsnov 	d = 0 $0 = 0$ $0 = 0$ $0 = 0$ $0 = 0$ $0 = 0$	o<0.1 25.33					

Figure 4: Regression with Newey-West standard errors: alcohol

crime_count	Coef.	St.Err.	t-	p-	[95%	Interval]	
			value	value	Conf		Sig
avgawnd	-2.233	0.391	-5.71	0.000	-3.001	-1.466	***
avgprcp	-18.138	4.380	-4.14	0.000	-26.724	-9.551	***
avgtmax	3.425	0.111	30.81	0.000	3.207	3.643	***
avgsnow	-15.048	3.603	-4.18	0.000	-22.110	-7.985	***
avgsnwd	-8.409	1.227	-6.85	0.000	-10.814	-6.004	***
edate	-0.112	0.002	-	0.000	-0.116	-0.107	***
			48.15				
holiday	-23.794	15.225	-1.56	0.118	-53.640	6.051	
OBS	-0.162	0.086	-1.89	0.059	-0.330	0.006	*
contral_c	11.504	0.854	13.47	0.000	9.830	13.177	***
change	63.443	7.129	8.90	0.000	49.467	77.419	***
Constant	2832.432	36.258	78.12	0.000	2761.356	2903.509	***
Mean dependen	t var 101	3.108	SD de	pendent v	var 263	.943	
Number of obs	697	9.000	F-test		138	9.508	
*** p<0.01, **	p<0.05, *p<	< 0.1					
(1) avgawnd							
(2) avgprcp =							
(3) avgtmax =							
(4) avgsnow							
(5) avgsnwd :	= 0						
. ,							
F(5,	6968) = 36 $cob > F =$	42.34 0.0000					

Figure 5: Regression with Newey-West standard errors: violent

-0.995 -13.138 2.233	0.209 2.653	-4.76 -4.95	value 0.000	Conf -1.404		Sig
-13.138	2.653		0.000	-1.404		
		-4 95		1	-0.585	***
2.233		7.75	0.000	-18.339	-7.938	***
	0.063	35.27	0.000	2.109	2.357	***
-5.543	1.257	-4.41	0.000	-8.007	-3.079	***
-3.990	0.577	-6.92	0.000	-5.121	-2.859	***
-0.038	0.001	-	0.000	-0.040	-0.035	***
		28.82				
12.363	6.154	2.01	0.045	0.299	24.427	**
-0.392	0.053	-7.45	0.000	-0.495	-0.289	***
5.437	0.442	12.31	0.000	4.571	6.303	***
8.369	4.079	2.05	0.040	0.374	16.364	**
1005.058	20.444	49.16	0.000	964.983	1045.134	***
var 417	.997	SD de	pendent v	var 119	.776	
697	9.000	F-test		984	.337	
	-3.990 -0.038 12.363 -0.392 5.437 8.369 1005.058	-3.990 0.577 -0.038 0.001 12.363 6.154 -0.392 0.053 5.437 0.442 8.369 4.079 1005.058 20.444	-3.990 0.577 -6.92 -0.038 0.001 - 28.82 12.363 6.154 2.01 -0.392 0.053 -7.45 5.437 0.442 12.31 8.369 4.079 2.05 1005.058 20.444 49.16	-3.990 0.577 -6.92 0.000 -0.038 0.001 - 0.000 28.82 12.363 6.154 2.01 0.045 -0.392 0.053 -7.45 0.000 5.437 0.442 12.31 0.000 8.369 4.079 2.05 0.040 1005.058 20.444 49.16 0.000	-3.990 0.577 -6.92 0.000 -5.121 -0.038 0.001 - 0.000 -0.040 28.82 12.363 6.154 2.01 0.045 0.299 -0.392 0.053 -7.45 0.000 -0.495 5.437 0.442 12.31 0.000 4.571 8.369 4.079 2.05 0.040 0.374 1005.058 20.444 49.16 0.000 964.983	-3.990 0.577 -6.92 0.000 -5.121 -2.859 -0.038 0.001 - 0.000 -0.040 -0.035 28.82 12.363 6.154 2.01 0.045 0.299 24.427 -0.392 0.053 -7.45 0.000 -0.495 -0.289 5.437 0.442 12.31 0.000 4.571 6.303 8.369 4.079 2.05 0.040 0.374 16.364 1005.058 20.444 49.16 0.000 964.983 1045.134

```
(2) avgprcp = 0

(3) avgtmax = 0

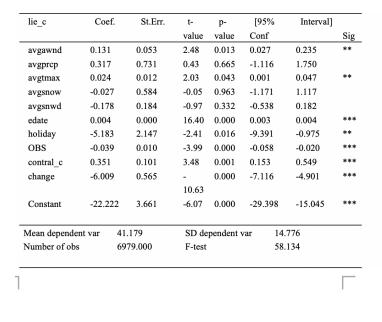
(4) avgsnow = 0

(5) avgsnwd = 0

F(5, 6968) = 407.56

Prob > F = 0.0000
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Figure 6: Regression with Newey-West standard errors: violent



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*** p<0.01, ** p<0.05, * p<0.1

(1) avgawnd = 0
(2) avgprcp = 0
(3) avgtmax = 0
(4) avgsnow = 0
(5) avgsnwd = 0
F( 5, 6968) = 3.08
Prob > F = 0.0088
```

Figure 7: Regression with Newey-West standard errors: deceptive behaviour

*** *** *** ***

Г

[95%

Interval]

 $theft_c$

Coef.

St.Err.

Figure 8: Regression with Newey-West standard errors: Theft

lrug_c	Coef.	St.Err.	t-	p-	[95%	Interval]	
			value	value	Conf		Sig
avgawnd	-0.303	0.116	-2.61	0.009	-0.531	-0.075	***
avgprcp	-4.257	1.135	-3.75	0.000	-6.482	-2.031	***
avgtmax	-0.069	0.029	-2.40	0.016	-0.126	-0.013	**
avgsnow	-3.374	0.749	-4.51	0.000	-4.842	-1.907	***
avgsnwd	0.085	0.281	0.30	0.763	-0.466	0.635	
							\Box
							L
edate	-0.026	0.000	-	0.000	-0.027	-0.025	***
			59.10				
holiday	-14.552	2.583	59.10 -5.63	0.000	-19.615	-9.490	***
	-14.552 0.088	2.583 0.018		0.000	-19.615 0.052	-9.490 0.123	***
holiday			-5.63				
holiday OBS	0.088	0.018	-5.63 4.80	0.000	0.052	0.123	***
holiday OBS contral_c	0.088 1.866	0.018 0.224	-5.63 4.80 8.34	0.000	0.052 1.427	0.123 2.305	***
holiday OBS contral_c change	0.088 1.866 42.546 544.148	0.018 0.224 2.492	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000	0.052 1.427 37.662 529.876	0.123 2.305 47.430	***
holiday OBS contral_c change Constant	0.088 1.866 42.546 544.148 ent var 10-	0.018 0.224 2.492 7.280	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***
holiday OBS contral_c change Constant fean depende fumber of ob	0.088 1.866 42.546 544.148 ent var 10-	0.018 0.224 2.492 7.280 4.471 79.000	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***
holiday OBS contral_c change Constant Mean depende Tumber of ob ** p<0.01, **	0.088 1.866 42.546 544.148 ent var 100 s 69' **p<0.05, **p	0.018 0.224 2.492 7.280 4.471 79.000	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***
holiday OBS contral_c change Constant Mean depende fumber of ob ** p < 0.01, ** (1) avgav	0.088 1.866 42.546 544.148 ent var 100 s 699 $\frac{1}{2}$ $\frac{1}{2}$ 1	0.018 0.224 2.492 7.280 4.471 79.000	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***
holiday OBS contral_c change Constant Mean depende fumber of ob ** p < 0.01, ** (1) avgav 2) avgprcp	0.088 1.866 42.546 544.148 ent var 100 s 699 *p < 0.05, *p wnd = 0 *p = 0	0.018 0.224 2.492 7.280 4.471 79.000	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***
holiday OBS contral_c change Constant Mean depende fumber of ob **p<0.01, ** (1) avgav 2) avgprcp 3) avgtmax	0.088 1.866 42.546 544.148 ent var 100 s 699 $\frac{1}{2}$ $\frac{1}{2}$ 1	0.018 0.224 2.492 7.280 4.471 79.000	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***
holiday OBS contral_c change Constant Mean depende fumber of ob **p<0.01, ** (1) avgav 2) avgprcp 3) avgtmax 4) avgsnov	0.088 1.866 42.546 544.148 ent var 100 s 69 $x^* p < 0.05, *p$ wnd = 0 x = 0 x = 0 x = 0	0.018 0.224 2.492 7.280 4.471 79.000	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***
holiday OBS contral_c change Constant Mean depende fumber of ob **p<0.01, ** (1) avgav 2) avgprcp 3) avgtmax 4) avgsnov 5) avgsnov 5) avgsnov	0.088 1.866 42.546 544.148 ent var 100 s 69 $x^* p < 0.05, *p$ wnd = 0 x = 0 x = 0 x = 0	0.018 0.224 2.492 7.280 4.471 79.000	-5.63 4.80 8.34 17.07 74.74	0.000 0.000 0.000 0.000	0.052 1.427 37.662 529.876 war 50.0	0.123 2.305 47.430 558.420	***

Figure 9: Regression with Newey-West standard errors: Drug Consumption

	0.205	0.050	1.20	0.655			
avgprcp	0.387	0.870	0.45	0.657	-1.319	2.093	***
avgtmax	0.102	0.017	5.95	0.000	0.069	0.136	**
avgsnow	-1.207	0.607	-1.99	0.047	-2.397	-0.018	**
avgsnwd	-0.139	0.249	-0.56	0.577	-0.626	0.349	***
date	-0.009	0.000	-	0.000	-0.009	-0.008	***
	Se .						
							ı
			29.24				_
holiday	3.924	2.752	1.43	0.154	-1.471	9.319	
OBS	-0.112	0.014	-8.21	0.000	-0.138	-0.085	***
contral c	1.098	0.146	7.52	0.000	0.812	1.384	***
change	2.992	1.316	2.27	0.023	0.413	5.571	**
-	239.204	5.121	46.71	0.000	229.166	249.242	***
Constant							
	ent var 81	.012	SD de	pendent	var 28.	397	
Constant Iean dependent Tumber of ob		.012 79.000	SD de F-test	-		397 3.799	
Iean depende		79.000		-			
tean dependerumber of obs ** p<0.01, ** (1) avgas	$p = \frac{69}{1000}$	79.000		-			
tean dependerumber of ob ** p<0.01, * (1) avgav 2) avgprcp	s 69 ** $p < 0.05$, * p wnd = 0 $p = 0$	79.000		-			
tean dependerumber of ob ** p<0.01, * (1) avgav 2) avgprep 3) avgtma:	s 69 ** $p < 0.05$, * p wnd = 0 $p = 0$ $p = 0$	79.000		-			
flean depender fumber of ob *** p<0.01, ** (1) avgav 2) avgprep 3) avgtma: 4) avgsnov	s 69 ** $p < 0.05$, * p wnd = 0 = 0 x = 0 v = 0	79.000		-			
fean depende fumber of ob ***p<0.01, * (1) avgan 2) avgprcp 3) avgtma: 4) avgsnov 5) avgsnw	s 69 ** $p < 0.05$, * p wnd = 0 = 0 x = 0 v = 0	79.000		-			

Interval]

0.217

Sig

[95%

Conf

-0.045

p-

0.199

value value

1.28

Regression with Newey-West standard errors

St.Err.

0.067

Coef.

0.086

sex_c

avgawnd

Figure 10: Regression with Newey-West standard errors: Sex

			varue	varue	Com		big
avgawnd	-0.087	0.007	-	0.000	-0.100	-0.073	***
-			12.39				
avgprcp	-0.336	0.081	-4.13	0.000	-0.496	-0.177	***
avgtmax	0.048	0.002	24.74	0.000	0.044	0.051	***
avgsnow	0.088	0.029	3.02	0.002	0.031	0.144	***
avgsnwd	-0.021	0.016	-1.30	0.193	-0.051	0.010	
edate	-0.001	0.000	_	0.000	-0.001	-0.001	***
			20.30				
							- 1
holiday	-0.269	0.118	-2.29	0.022	-0.499	-0.038	**
OBS	0.006	0.002	3.56	0.000	0.003	0.009	***
contral_c	0.086	0.016	5.34	0.000	0.054	0.117	***
change	1.454	0.143	10.19	0.000	1.174	1.734	***
Constant	11.109	0.544	20.41	0.000	10.042	12.177	***
Mean depende	ent var 2.	088	SD de	pendent	var 2.3	380	
Number of ob	s 69	79.000	F-test		14	0.359	
*** p<0.01, *	*<0.05 *-	- < 0.1					
p<0.01,	p < 0.05, $p < 0.05$	0.1					
(1) avgawne	d = 0						
(2) avgprcp	= 0						
(3) avgtmax							
(4) avgsnov							
(5) avgsnwo							
		169.82					
	Prob > F =	0.0000					
ı	1100 / F -	0.0000					

Coef. St.Err. t- p- [95%

value value Conf

Interval]

Sig

Regression with Newey-West standard errors

game_c

Figure 11: Regression with Newey-West standard errors:gambling

ht c	Coef.	St.Err.	t-	p-	[95%	Interval]	
			value	value	Conf		Sig
avgawnd	0.000	0.000	-0.78	0.438	-0.001	0.000	
avgprcp	0.004	0.005	0.74	0.460	-0.006	0.014	
avgtmax	0.000	0.000	0.12	0.905	0.000	0.000	
avgsnow	-0.002	0.001	-2.15	0.032	-0.004	0.000	**
avgsnwd	-0.001	0.000	-1.28	0.199	-0.002	0.000	
edate	0.000	0.000	4.97	0.000	0.000	0.000	***
holiday	0.002	0.011	0.16	0.873	-0.019	0.023	
OBS	0.000	0.000	-1.64	0.100	0.000	0.000	
contral_c change Constant	0.000 -0.011 -0.143	0.001 0.002 0.030	0.76 -5.94 -4.79	0.450 0.000 0.000	-0.001 -0.014 -0.202	0.002 -0.007 -0.085	***
change	-0.011 -0.143	0.002	-5.94 -4.79	0.000	-0.014 -0.202	-0.007	***
change Constant Mean dependen Number of obs	-0.011 -0.143 t var 0.69	0.002 0.030 009 079.000	-5.94 -4.79	0.000 0.000 pendent	-0.014 -0.202 var 0.0	-0.007 -0.085	***
change Constant Mean dependen Number of obs *** p<0.01, ** (1) avgawr (2) avgprcp = (3) avgtmax =	$ \begin{array}{c c} -0.011 \\ -0.143 \\ \hline t var & 0. \\ 69 \\ \hline p < 0.05, *_{f} \\ ad = 0 \\ = 0 \\ = 0 $	0.002 0.030 009 079.000	-5.94 -4.79 SD de	0.000 0.000 pendent	-0.014 -0.202 var 0.0	-0.007 -0.085	***
change Constant Mean dependen Number of obs *** p<0.01, ** (1) avgawr (2) avgprep = (3) avgtmax = (4) avgsnow =	$ \begin{array}{c c} -0.011 \\ -0.143 \\ \hline t var & 0. \\ 65 \\ \hline p < 0.05, *_{f} \\ ad = 0 \\ = 0 \\ = 0 \\ = 0 $	0.002 0.030 009 079.000	-5.94 -4.79 SD de	0.000 0.000 pendent	-0.014 -0.202 var 0.0	-0.007 -0.085	***
change Constant Mean dependen Number of obs *** p<0.01, ** (1) avgawr (2) avgprep = (3) avgtmax = (4) avgsnow = (5) avgsnwd =	$ \begin{array}{c c} -0.011 \\ -0.143 \\ \hline t var & 0. \\ 65 \\ \hline p < 0.05, *_{f} \\ ad = 0 \\ = 0 \\ = 0 \\ = 0 $	0.002 0.030 009 079.000	-5.94 -4.79 SD de	0.000 0.000 pendent	-0.014 -0.202 var 0.0	-0.007 -0.085	***

Figure 12: Regression with Newey-West standard errors:human traffic

chrildren_c	Coef.	St.Err.	t-	p-	[95%	Interval]	
			value	value	Conf		Sig
avgawnd	-0.050	0.014	-3.67	0.000	-0.077	-0.023	***
avgprcp	-0.939	0.166	-5.65	0.000	-1.265	-0.613	***
avgtmax	0.034	0.003	11.03	0.000	0.028	0.040	***
avgsnow	-0.125	0.080	-1.56	0.118	-0.282	0.032	
avgsnwd	-0.008	0.035	-0.23	0.814	-0.076	0.060	
edate	-0.001	0.000	-	0.000	-0.001	-0.001	***
			24.97				
holiday	-0.594	0.257	-2.31	0.021	-1.098	-0.090	**
							_
							L
OBS	0.038	0.003	14.60	0.000	0.033	0.043	***
contral_c	0.117	0.026	4.53	0.000	0.067	0.168	***
contral_c change	0.117 2.502	0.026 0.230		0.000 0.000	0.067 2.051	0.168 2.953	***
contral_c	0.117	0.026	4.53	0.000	0.067	0.168	
contral_c change Constant	0.117 2.502 25.678	0.026 0.230 0.919	4.53 10.88 27.93	0.000 0.000 0.000	0.067 2.051 23.876	0.168 2.953 27.480	***
contral_c change	0.117 2.502 25.678 nt var 7.	0.026 0.230	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953	
contral_c change Constant Mean depender Number of obs	0.117 2.502 25.678 nt var 7.	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	
contral_c change Constant Mean depender	0.117 2.502 25.678 nt var 7.	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	
contral_c change Constant Mean depender Number of obs *** p<0.01, **	0.117 2.502 25.678 nt var 7.	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	***
contral_c change Constant Mean depender Number of obs *** p<0.01, ** (1) avgawnd	0.117 2.502 25.678 nt var 7. ϵ $p < 0.05, *p$ $= 0$	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	***
contral_c change Constant Mean depender Number of obs *** p<0.01, ** (1) avgawnd (2) avgprop	0.117 2.502 25.678 Int var 7. ϵ *p < 0.05, *p = 0 = 0	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	***
contral_c change Constant Mean dependen Number of obs *** p<0.01, ** (1) avgawnd (2) avgprop (3) avgtmax	0.117 2.502 25.678 Int var 7. ϵ *p < 0.05, *p = 0 = 0 = 0	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	***
contral_c change Constant Mean dependen Number of obs *** p<0.01, ** (1) avgawnd (2) avgprop (3) avgtmax (4) avgsnow	0.117 2.502 25.678 Int var 7. 6 p < 0.05, *p = 0 = 0 = 0 = 0	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	***
contral_c change Constant Mean dependent Number of obs ***p<0.01, ** (1) avgawnd (2) avgprop (3) avgtmax (4) avgsnow (5) avgsnwd	0.117 2.502 25.678 Int var 7. 6 p < 0.05, *p = 0 = 0 = 0 = 0	0.026 0.230 0.919 112 5979.000	4.53 10.88 27.93	0.000 0.000 0.000 pendent	0.067 2.051 23.876 var 3.8	0.168 2.953 27.480	***

Figure 13: Regression with Newey-West standard errors:children relative crime

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