Evaluating the Effectiveness of Blue Light Cameras in Rochester

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ABSTRACT

The purpose of this research is to evaluate the effectiveness of Rochester's blue light cameras in controlling crime. After time series analysis on general crime trend and counter map analysis of crime distribution, we decide to do camera impact analysis on different sections in Rochester. Then we give an overall impact of cameras and list effective and non-effective camera locations plus a case analysis. The method used in this research including the rate of change, Wilcoxon test, etc. Conclusion of this paper is that cameras have a modest but measurable effect on reducing crime in Rochester.

1. INTRODUCTION

The first batch of 50 cameras was purchased and installed in Rochester in 2008. Up to 2010, a total number of 82 cameras were installed and the current number of cameras in Rochester is 136. According to the mayor of Rochester, this city now is having the lowest crime rate in past 30 years. The goal of this research is to find the hidden relation between the camera installation and crime decreasing.

As the monitoring, all the cameras are monitored live by the police department, but only a fraction of them can be monitored live due to the limited human resource, but the footage is saved for later review in investigations.

There are two kinds of cameras in Rochester: red light cameras and blue light cameras. Red light cameras are speed cameras and traffic cameras; street cameras are called blue light cameras, which installed at troubled street corners to combat all kinds of crimes. Another find is that there's no camera in some areas such as areas near to University of Rochester and Rochester Institute of Technology.

2. RELATED WORK

La Vigne et al. (2013) apply Difference-in- Differences (DiD) analyses and descriptive analyses to do time series analysis of pre- and post-intervention reported crimes in each camera area to detect the degree to which cameras had an impact on crime. They also do spatial analyses of potential displacement and diffusion effects in areas adjacent to the camera locations [1].

Hemming et al. (2004) and Schwartz et al. (2012) are both involving with analyzing CCTV effectiveness via categorizing different types of crimes and obtain the same results that CCTV have a different impact for different types of incidents [2] [3].

Bowers, Kate J et al. (2003) focus on the decay effectiveness of cameras impact on crime controlling – not only the decay in time but also decay in distance.

3. DATA COLLECTION

Available data in this research including Camera installation locations and dates, Crimes, geocoded into shape files, Camera room policies, etc. We encode the original shapefile data to extract the camera (location) data, which including targeted attributes latitude, longitude, and add installation-time attribute via integrating different sources of information. We also clean the crime data of Rochester from 2005 to 2016 which also including latitude, longitude, and other useful attributes. An example of camera data and crime data are in the appendix. Some data are download from Rochester police department open data portal http://data-rpdny.opendata.arcgis.com/.

4. EXPLORATORY ANALYSIS

4.1 Crime Data Exploration

4.1.1 Time series analysis

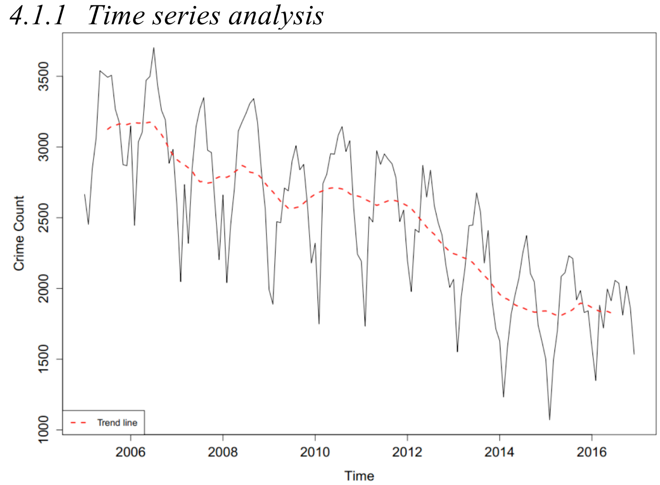

Figure 1. Crime count from 2005 to 2016 of Rochester

From figure 1 we can observe a general decreasing trend of crime count from 2005 to 2016. Besides, crime data present an obvious cyclical trend – every year crime count reaches the peak at summer, then start to peak off in a cycle. The red dashes line is trend line.

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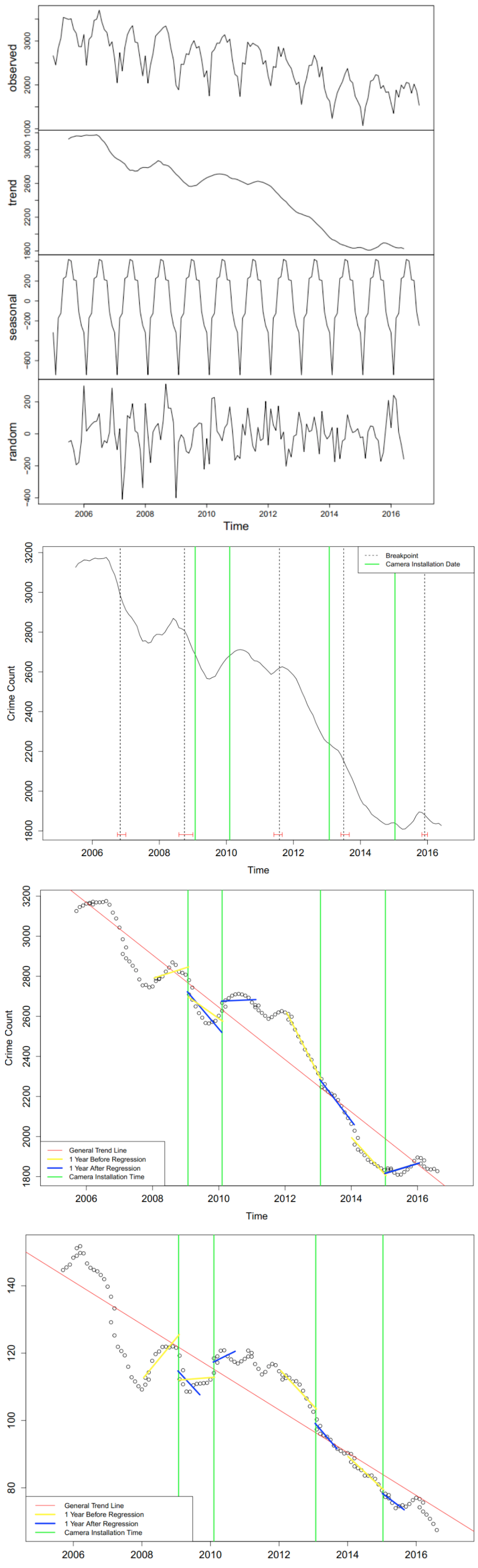


Figure 2. First: Decomposition of additive time series; Second: Real trend with breakpoint; Third: Real trend regression of all crime; Forth: Real trend regression of camera nearby crime (a sample)

There are two approaches to decompose the zigzag raw crime count, the first part 'observed' in first figure - multiplicative and additive. In multiplicative mode: observed = trend * seasonal * random, whereas in additive mode: observed = trend + seasonal + random. Both approaches were performed and obtained similar decomposition results. For simplicity, here we chose additive decomposition method.

After eliminating observed trend, random trend and seasonal trend, we can see the breakpoint of the real trend in the second figure. We also add four main camera installation date showing as green auxiliary lines to figure out their relationship with breakpoints, from which we can observe a structural change.

From figure third and figure forth, we can see that crime count near cameras (in this sample) shows a similar trend with the general crime count over the city (the population). And some trend changes were observed around camera installation time. The most significant one is the batch installed in 2009.

4.1.2 Crime type analysis

In total, there are 33 types of crimes, here we list the top 10 crimes.

Table 1. Top 10 crime types.

Crime Type	**Number**
larceny	84306
simple assault	62657
criminal mischief	50135
all other offenses (except traffic)	32082
burglary	30379
controlled substances	20185
mv theft	13101
aggravated assault	12099
disorderly conduct	10808
robbery	10730

From table 1 we can see that crimes are not evenly distributed by crime types in Rochester, which inspire us to do further research on analyzing camera effectiveness based on crime types.

4.2 Camera Data Exploration

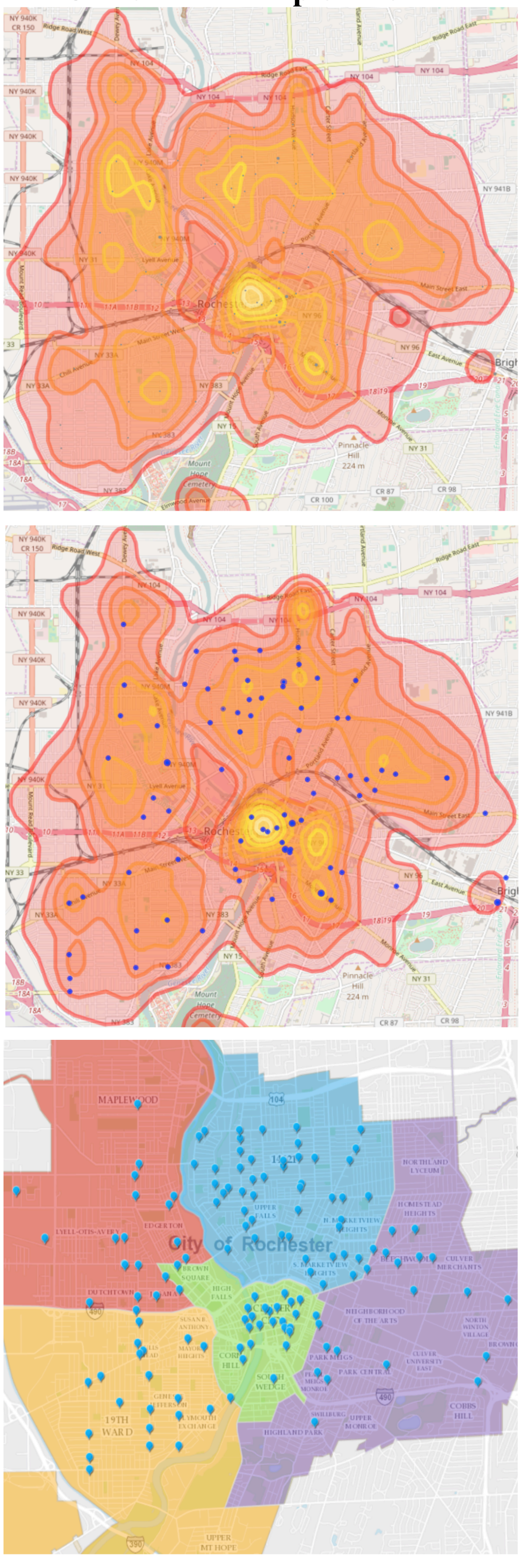


Figure 3. Top: Counter map of crime (Year: 2005- 2008); Middle: Counter map of crime (Year: 2009-2012); those blue points are locations of cameras); Bottom: Map of five section in Rochester

From the comparison of these two time periods (Using 2008 as the cutoff point, backward and forward 4 hours separately. First, we can find that there's obvious density decrease in some part that has been surrounded by cameras now. In addition, there's also a situation of crime distribution skewness, which means that there's a possibility that cameras have an effect on pushing crimes to places without cameras. Besides, when comparing with the administrative division map in Rochester, we can find that the distribution of crimes is highly overlapping with the sectional division in Rochester (further explanation of sectional division map is the appendix). So the next step of research is diving cameras and crimes according to five sections areas in Rochester.

Table 2. Cameras count in different sections

Sections	Number of Cameras
boundary	6
section_1	33
section_3	23
section_5	23
section_7	55
section_9	30

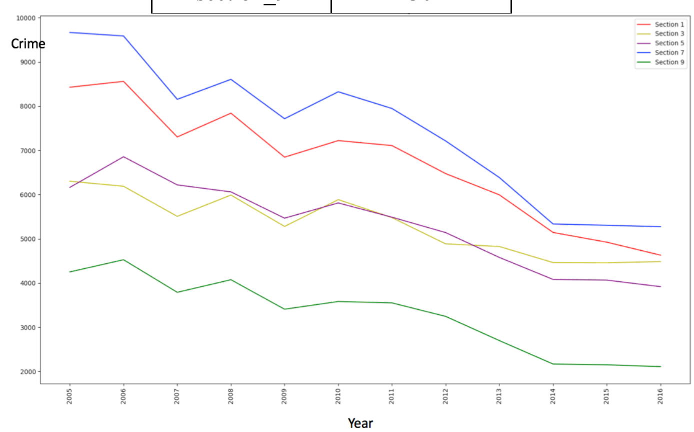


Figure 4. Crime count in different sections by year

Sections 7 has the most crime, correspondingly it has the most number of cameras. The number of cameras in section 3 and section 5 is same and their crime count is at the same level. Interestingly, section 9 has the lowest crime count comparing with other sections, whereas the number of cameras in section 9 is at the mediocre level, which is more than section 3 and section 5 that has more crime number.

5. METHODS

5.1 Wilcoxon Rank Sum Test

Conventions differ regarding the implementation of the rank sum test, however, most approaches can be based on the following. Define F_1 as the sum of ranks from sample 1, F_2 as the sum of ranks from sample 2. Here we are actually testing:

$$H_0: F_1(x) = F_2(x) \quad H_1: F_1(x) \geq F_2(x) \qquad \text{or} \qquad H_0: F_1(x) = F_2(x) \quad H_1: F_1(x) \leq F_2(x)$$

where $F_j(x)$ is the distribution function for j = 1,2. Conducting this test is similar to conducting a permutation test. The steps are detailed below.

1. Assume that no two observations have the same value so that the ranks are distinct. We will discuss shortly how to deal with "ties" in the data. Also, assume that F_1 has m observations and F_2 has n observations.
2. Combine the m + n observations into one group and rank the observations from smallest to largest. Find the observed rank sum, W, of F^1.
3. Find all the possible permutation of the ranks into which m ranks are assigned to F_1 and n ranks are assigned into F_2.
4. For each permutation of the ranks, find the sum of the ranks for F_1.
5. Determine the p-value:

$$P_{upper} = \frac{number\ of\ rank\ sums \leq observed\ ranks\ sum\ W}{\binom{m+n}{n}}$$

5.2 Rate of Change

Consider the case where the numerator f of a rate is a function f(a) where a happens to be the denominator of the rate. A rate of change of f with respect to a (where a is incremented by h) can be formally defined in two ways:

$$Average\ rate\ of\ change = \frac{f(a+h)-f(a)}{h}$$
$$Instantaneous\ rate\ of\ change = \lim_{h\to 0}\frac{f(a+h)-f(a)}{h}$$

where f(x) is the function with respect to x over the interval from a to a+h. An instantaneous rate of change is equivalent to a derivative. In this research h is time period, f(x) is crime count during this period.

5.3 Count of Crime

Buffer areas are used to count crime according to radius. Within each area, we tested for statistically significant changes in average yearly crime counts within: (1) buffer zones of 50 meter; (2) buffer zones of 100 meter; (3) buffer zones of 150 meter; and (4) buffer zones of 300 meter.

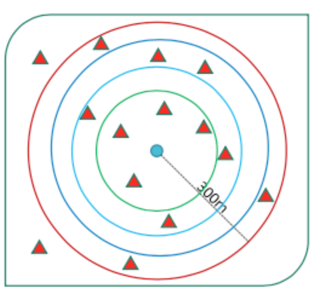


Figure 5. Map of buffer areas. The red triangle represents crime count; the green circle is (1) buffer zone; the light blue circle is (2) buffer zone; the dark blue circle is (3) buffer zone; the red circle is (4) buffer zone.

6. ANALYSIS AND RESULTS

6.1 Section Seven Analysis

Section 7, the Clinton section has the most crime, as well as the most number of cameras. So we choose section seven to do yearly rate of change of crimes analysis.

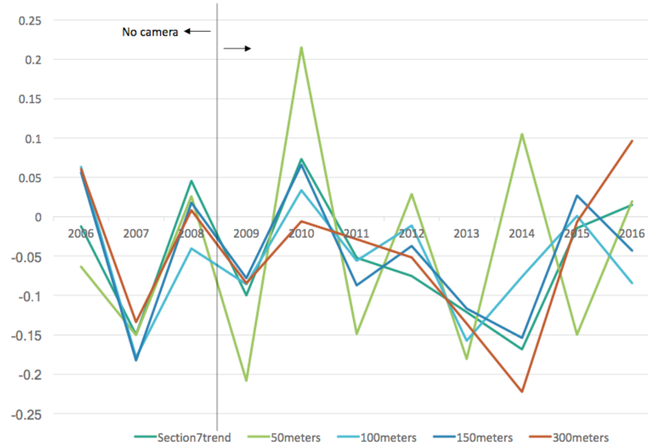


Figure 6. Yearly Rate of Change of Crimes in City Section 7 (Clinton)

From figure 6, we can see that before camera installation, the change of rate at different buffer areas are highly same, also are very similar with the section 7 general trend. Within the increasing in the number of cameras, crimes in the buffer zone of 50 meters start to wiggle widely, whereas crimes in other buffer zones still in accordance with the general trend of section 7.

6.2 All Sections Analysis

Applying change of rate method, set year 2005 to 2009.01 as part 1, year 2009.01 to year 2012 as part 2. The formula used here is

$$Rate\ of\ change = \frac{Part2 - Part1}{Part1}$$

Table 3. Sectional analysis of rate of change of different crime types (part)

	All Crime	larceny	simple assault	criminal mischief	controlled substances
Section1	-0.14157	-0.13847	0.100487	-0.06366	-0.12794
9 Cameras S1	-0.30844	-0.14458	-0.36111	-0.24528	0.025
Section3	-0.1052	-0.05516	0.169746	-0.06962	-0.12313
12 Cameras S3	-0.10158	0.09434	0.139344	-0.04225	-0.13333
Section5	-0.13904	-0.07402	0.206359	-0.08977	-0.22857
12 Cameras S5	-0.12266	0.401361	0.095652	-0.17391	-0.35652
Section7	-0.13998	0.043791	0.033642	-0.1009	-0.18952
33 Cameras S7	-0.26682	0.131868	-0.12971	-0.17333	-0.41935
Section9	-0.16638	-0.10232	0.033236	-0.19942	-0.0048
16 Cameras S9	-0.01553	-0.19694	0.417476	-0.26263	0.2
City Wide	-0.13723	-0.06544	0.104105	-0.0949	-0.15562
ALLCameras (82)	-0.15731	-0.02113	0.055696	-0.18065	-0.24905

Red one means has an effect, black one means has no effect. For example, for 9 cameras in section 1, cameras have effect in reducing crimes for all crime types other than controlled substances The full table is in the appendix.

6.3 Wilcoxon Test

Again, if use crime data before installation as part 1, crime data after installation as part 2 to do Wilcoxon test, the hypothesis here is:

$$H_0: Part\ 1 \leq Part\ 2$$
$$H_1: Part\ 1 \geq Part\ 2$$

The result of these 82 cameras are:

Number of Cameras	Reject	Fail to Reject
82	42	40

Table 4. Result of Wilcoxon test of 82 cameras

Then we project the Wilcoxon test result to crime contour map in two different time periods.

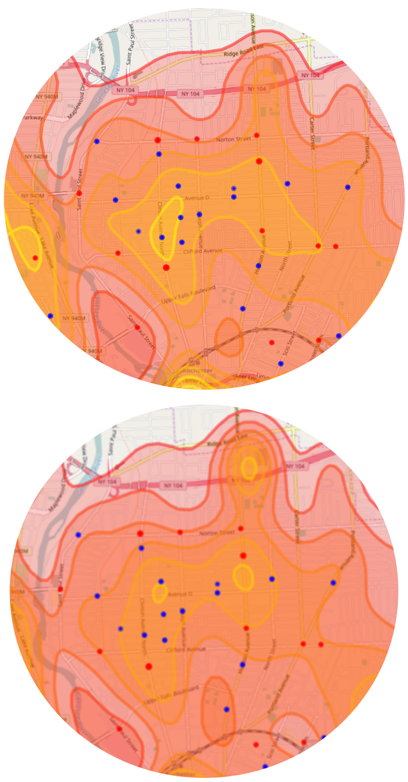


Figure 7. Top: Section7 Contour Map of Crimes (Year:2005-2008); Bottom: Section7 Contour Map of Crimes (Year:2009-2012); red points are fail test points, pass test are pass test points

We can see that near the pass test points, crime density significantly decrease; while near the failed test points, the change of density is not that obvious.

6.4 Case Analysis

Then we project the effective cluster and ineffective cluster to different crime types.

Table 5. Crime by type for effective and ineffective cameras

Crime Type	Effective Cluster	Ineffective Cluster
controlled substances	195	140
simple assault	152	115
criminal mischief	109	85
larceny	96	141
all other offenses	66	58
disorderly conduct	66	45
aggravated assault	62	32
robbery	57	31
burglary	55	45
mv theft	34	15

Only larceny crime type has more crime controlling in ineffective camera cluster, other crime types all have more crime controlling in the effective cluster. Then we give two examples of reject hypothesis and fail to reject hypothesis.

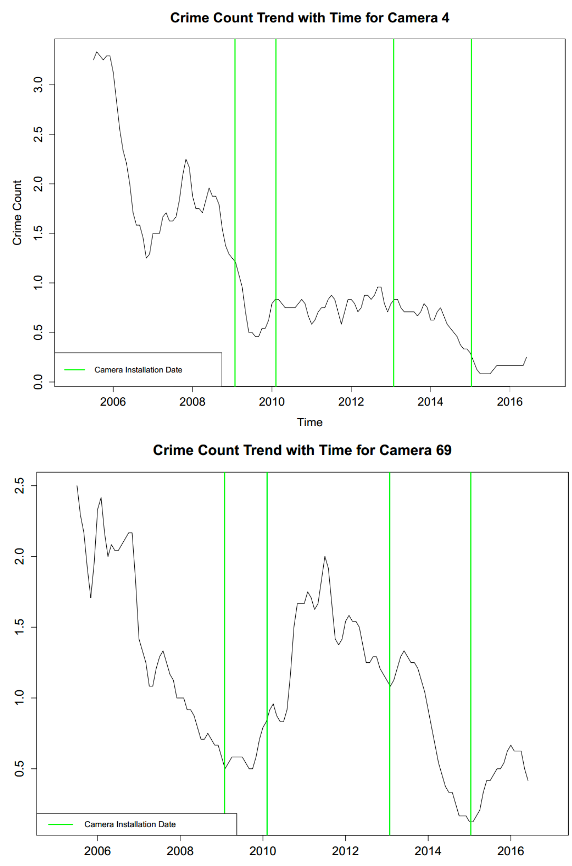


Figure 8. Top: reject hypothesis example; Bottom: fail to reject Hypothesis example

Here we chose the example camera 4 to stand for reject hypothesis, and camera 69 to stand for fail hypothesis example. We can see that camera 4 has a more stable decreasing trend, and the camera 69 has a more fluctuant trend. There are also big turns in installation date. Then we give crime yearly count around effective clusters and ineffective clusters.

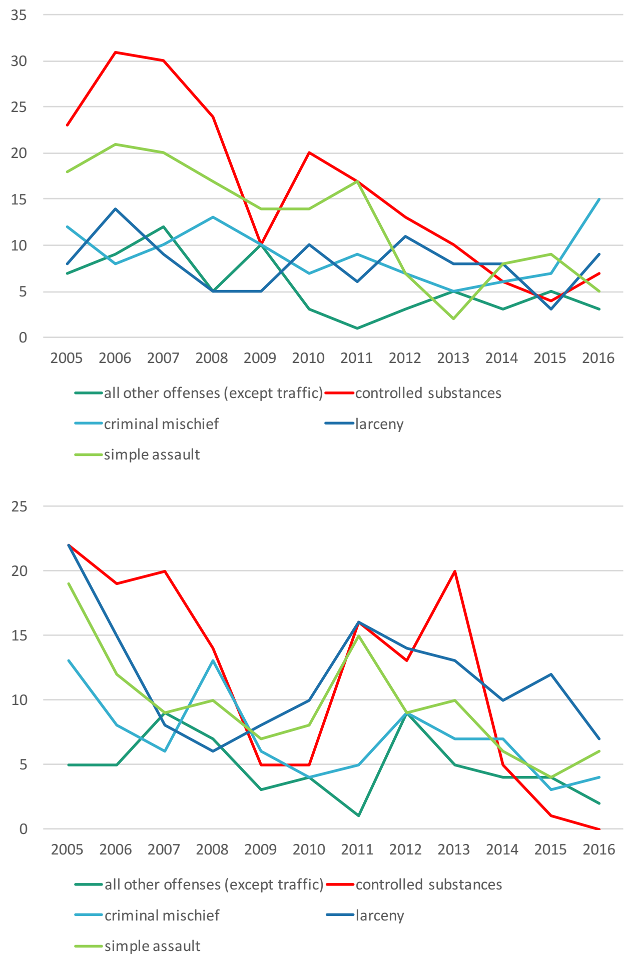


Figure 9. Top: crime yearly count around effective clusters; Bottom: crime yearly count around ineffective clusters

It can also find that in effective clusters, the decreasing trend is stable in effective clusters, and more fluctuant in ineffective clusters. Besides, different crime types have different wiggle level.

7. CONCLUSION

Some Bluelight cameras installed in Rochester were observed to help deter crimes through two approaches - directly decrease crime count in adjacent areas; skew distribution of crimes

However, nearly a half of cameras that were installed before 2011 did not see a significant decrease in crime around the location.

Effective cameras have a higher probability to appear as a cluster. Ineffective cameras are more likely to be on main streets.

Certain crime types are more sensitive to the presence of cameras (e.g. crimes involve controlled substance).

8. FUTURE WORK

First, based on our analysis, to find future candidate camera installation locations and find which cameras can be removed. Second, for the effective cameras, try to find if there are any decay effects with time. Third, if control group can be found, it will be an entry point to conduct DID analysis.

9. ACKNOWLEDGMENTS

First, we would like to extend gratitude to our supervisor, Mr. Kirk Ocke, for his instructive advice and useful suggestions on our report. We are deeply grateful for his help in the completion of this research.

High tribute shall be paid to Mr. Adrian Martin from Rochester Police Department, who gave us lots of great advice.

10. REFERENCES

[1] Rochester police department open data portal. URL: http://data-rpdny.opendata.arcgis.com/

[2] La Vigne, Nancy G., et al. "Evaluating the use of public surveillance cameras for crime control and prevention." Washington, DC: US Department of Justice, Office of Community Oriented Policing Services. Urban Institute, Justice Policy Center (2011).

[3] Gill, Martin, and Martin Hemming. "Evaluation of CCTV in the London borough of Lewisham." Leicester, UK: Perpetuity Research & Consultancy International (PRCI) (2004).

[4] Schwartz, Adam. "Chicago's video surveillance cameras: A pervasive and poorly regulated threat to our privacy." Nw. J. Tech. & Intell. Prop. 11 (2012): ix.

[5] Lawhead, Joel. Learning geospatial analysis with Python. Packt Publishing Ltd, 2015.

[6] ESRI, ESRI. "Shapefile Technical Description, Jul. 1998."

[7] Bowers, Kate J., and Shane D. Johnson. "Measuring the geographical displacement and diffusion of benefit effects of crime prevention activity." Journal of Quantitative Criminology 19.3 (2003): 275-301.

[8] Cameron, Aundreia, et al. "Measuring the effects of video surveillance on crime in Los Angeles." Californian Research Bureau, University of Southern California: School of Policy Planning and Development (2008).

[9] Gill, Martin. 2006. “CCTV: Is It Effective?” In The Handbook of Security, edited by Martin Gill, 438–461. New York: Palgrave Macmill

11. APPENDIX

11.1 Example Data

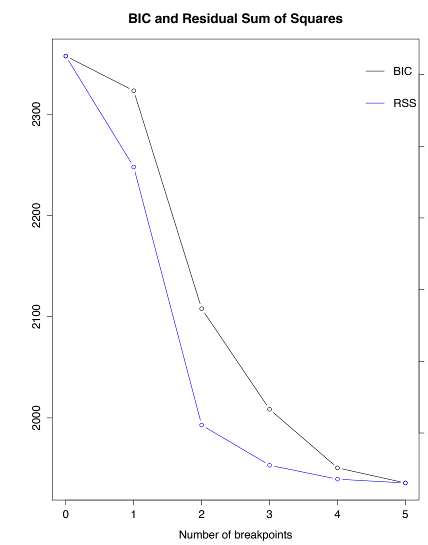
Table 6. Example data of camera

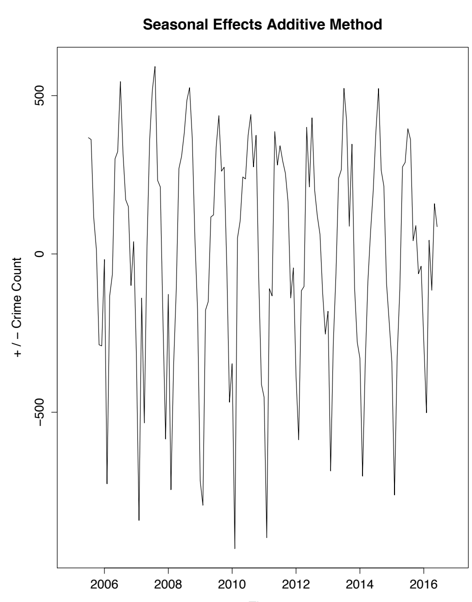
X	Y	OBJECTID	Address	Type	Program	Year	Month	section
-77.6127	43.17339	3	N Clinton Ave and Scrantom St	Video	BlueLight	2009	7	7
-77.6031	43.18073	4	Ave D and Bauman St	Video	BlueLight	2009	7	7

Table 7. Example data of crime

FullAddress	Lat	Lon	CrimeType	Section	Occur Date	OffenseDOW	OffenseMonth	OffenseQuarter	OffenseYear	RPDPlatoon
810 BROWN ST	43.15069	-77.6355	BURGLARY	3	2/1/2005	Wednesday	February	1	2005	1
501 GENESEE ST	43.14028	-77.6372	LARCENY	3	2/1/2005	Wednesday	February	1	2005	3

11.2 Time series supplement





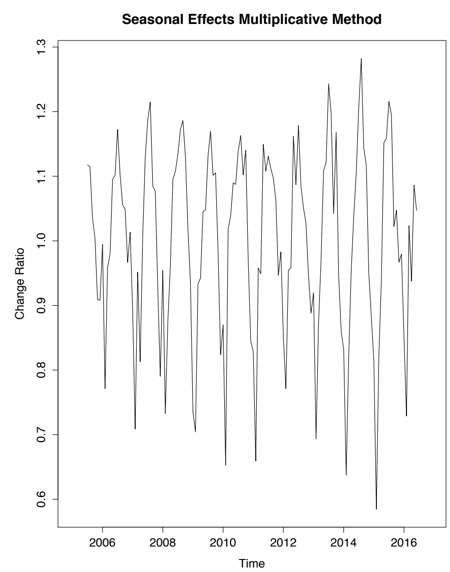


Figure 10. Supplement of time series analysis

On the first figure, the BIC and RSS score shows that there are 5 structure pattern changes in the real trend.

11.3 Sectional analysis

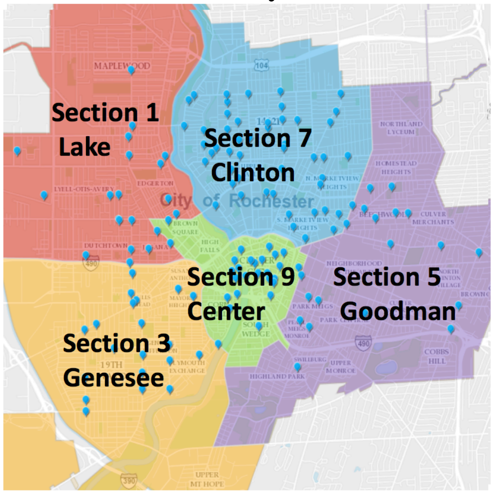


Figure 11. Rochester sectional division map

Table 8. Sectional analysis of rate of change of different crime types (full)

	All Crime	larceny	simple assault	criminal mischief	controlled substances	burglary	aggravated assault	all other offenses (except traffic)	dangerous weapons	disorderly conduct	mv theft	robbery
Section1	-0.14157	-0.13847	0.100487	-0.06366	-0.12794	0.03925	0.012987	-0.5165	-0.34037	0.02991	-0.52017	-0.2976
9 Cameras S1	-0.30844	-0.14458	-0.36111	-0.24528	0.025	-0.17073	-0.58621	-0.40323	-0.25	-0.35294	-0.69565	-0.6
Section3	-0.1052	-0.05516	0.169746	-0.06962	-0.12313	0.247227	-0.04251	-0.48387	-0.41399	0.004566	-0.55111	-0.33976
12 Cameras S3	-0.10158	0.09434	0.139344	-0.04225	-0.13333	0.205882	-0.38462	-0.34483	-0.5	-0.2381	-0.45	-0.36667
Section5	-0.13904	-0.07402	0.206359	-0.08977	-0.22857	0.191805	-0.10837	-0.54693	-0.315	-0.24077	-0.64416	-0.21429
12 Cameras S5	-0.12266	0.401361	0.095652	-0.17391	-0.35652	0.228571	-0.51351	-0.07143	-0.33333	-0.28049	-0.66667	-0.68421
Section7	-0.13998	0.043791	0.033642	-0.1009	-0.18952	-0.01762	-0.03294	-0.4591	-0.31796	-0.11332	-0.61054	-0.2699
33 Cameras S7	-0.26682	0.131868	-0.12971	-0.17333	-0.41935	-0.27711	0.02439	-0.16667	-0.39474	-0.5	-0.57143	-0.60345
Section9	-0.16638	-0.10232	0.033236	-0.19942	-0.0048	-0.2679	-0.06122	-0.49098	-0.23077	0.35443	-0.62776	-0.38147
16 Cameras S9	-0.01553	-0.19694	0.417476	-0.26263	0.2	-0.5641	0.266667	-0.12121	0	1.315315	-0.75	-0.45238
City Wide	-0.13723	-0.06544	0.104105	-0.0949	-0.15562	0.065697	-0.03608	-0.49933	-0.33914	0.016888	-0.58982	-0.28952
ALLCameras (82)	-0.15731	-0.02113	0.055696	-0.18065	-0.24905	-0.15948	-0.18894	-0.19617	-0.36145	0.052752	-0.62827	-0.57037

Red one means has effect, black one means has no effect. For example, for 9 cameras in section 1, cameras have effect in reducing crime for all crime types other than controlled substances, dangerous weapons, and robbery.

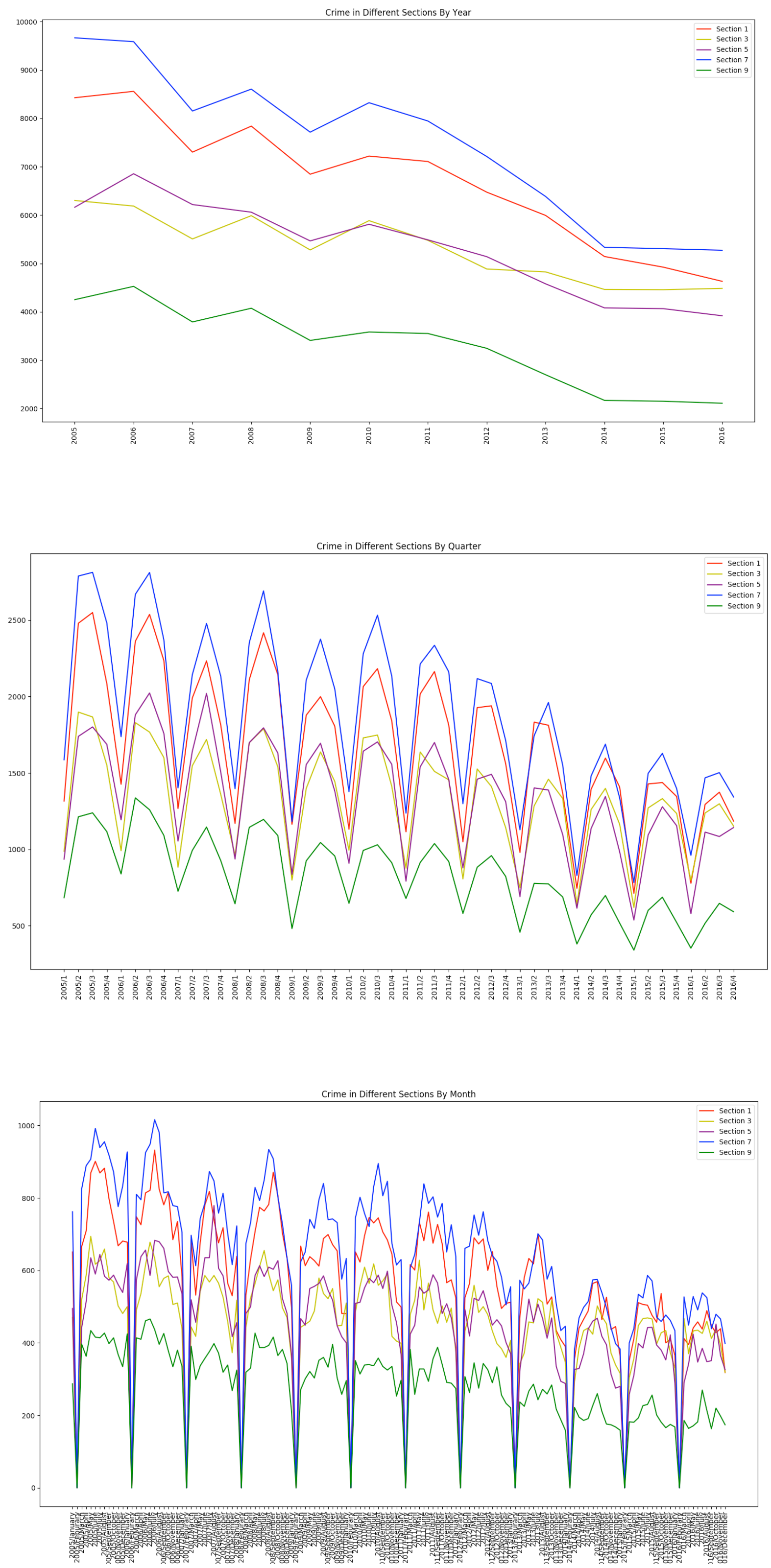


Figure 12. Crime in different section by year, quarter, moth