Breaking Windows:
A Study of Crime and Parking Tickets in New York City

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Abstract

This paper takes an in-depth look at New York City crime and parking tickets. The theory behind the paper stems from the New York Police Department's continued use and defense of "broken windows" policing. Broken windows describes the theory that if a community enforces low-level crimes such as removing graffiti and turnstile jumping, then the rate at which major crimes are committed will decrease. The purpose of this paper is to examine whether parking violations can be seen as a minor crime in this framework. Marc Weiss, professor at Walden University, wrote his dissertation on the effects that traffic enforcement, such as ticketing speeding, have on crime. In the study, Weiss found a strong negative correlation, implying that enforcing more traffic violation would indeed lessen the crime rate. Using this research as a springboard, I decided to see if I could get similar results by substituting parking tickets for traffic stops. After using data from New York City, I found that there was a significant positive correlation between parking tickets and crime. This positive trend can be seen on the entire city, as well as on a borough and precinct level. This shows that parking tickets do not follow traffic enforcement, as the increase in parking tickets will increase crime. After dividing the datasets into different types of crimes, I found that the more violent the crimes, the less strong the positive correlation was. After finding this correlation I went on to find other relationships in the data. There is no correlation between the day of the month and the likelihood of getting a ticket. I also found that as temperature rises, crime rates rise too, and as humidity and precipitation increase, tickets and crimes decrease.

1. Introduction

The theory of Broken Windows Policing has been a hot topic of conversation over the past few decades. In the early 1980's, political-scientist James Q. Wilson and criminologist George L. Kelling worked together to understand crime on a fundamental level. In their research, they came up with a theory they called "broken windows". This theory states that public disorder and crimes are positively correlated: as there is more disorder in a community, more crimes will be committed. Wilson and Kelling use an example of a town with one broken window. If that window is not repaired, it will signal that people do not care about the property in the area, and will encourage more windows to be broken. Eventually, all the windows in the community will be broken and there will be an increase in crime. Wilson and Kelling argue for a stronger police force that maintains order in society to protect the community. Under their theory, a police force that enforces minor crimes will maintain the peace, which will lead to an overall safer community [21].

In the late 1980's, the broken windows theory lacked substantial evidence. This theory needed to be tested in a real world setting to truly see how effective it could be. In 1989, the Mass Transit Authority (MTA) of New York tried to understand the rapid decline in the rate at which the subway system was used. They saw that in the recent history, fewer people were using the subway. The MTA had heard of the broken windows theory and brought in George Kelling to help them adress their problem. When Kelling went down into the subway system, he witnessed pure disorder: rampant homelessness and graffiti. This was an opportunity for Kelling to put his theory to action. Kelling, with the help of the MTA and NYPD, removed the graffiti and homelessness in the subway system and as a result, brought order to subways system [11]. The "Take back the subway" campaign was the first step in a growing trend to curb crime in New York.

From 1994 to 1996, William Bratton, a staunch advocate of broken windows theory, served as the police commissioner for New York City. During his tenure, Bratton implemented more active policing laws by cracking down on public drunkenness, turnstile jumping, and aggressive panhandling [8]. In 1998 Kelling and Bratton wrote a piece together describing how they used broken windows policing to make New York City a safer place [12]. Through their efforts, New York City was made a much safer place for tourists and residents. From 1990 to 1999, overall crime in New York City dropped from 1.1 million to 600 thousand crimes committed annually. This falling trend could be seen across all types of crimes, from murder and rape to burglary and theft [3].

While this picture of broken windows looks convincing, the evidence has caused skepticism, especially in academic spheres. Bernard Harcourt, critical theorist at Columbia University, is one of the major critics of broken windows theory, and argues that there are problems with broken windows policing. In his work, Harcourt focuses on the underlying research done by Wilson and Kelling and their reliance on the work of Wesley Skogan. In analyzing Skogan results further, Harcourt found that adjusting for poverty, stability, and race eradicated any significant correlations. In addition, Harcourt argues that the decline in crime during Bratton's tenure was a result of economic conditions, a decline in the use of crack, fewer 18-24 year old males, and a larger police force [8]. In Harcourt's eyes, the major drop in crime in the 1990's was due to systemic changes, not the work of Bratton and the NYPD and their implementation of the broken windows theory.

In 1998, Gary Stewart wrote in the Yale Journal about the racial impacts of broken windows policing. Stewart did not focus on the effectiveness of broken windows policing, but rather agued that the policy itself is inherently biased. While broken windows may decrease the crime level, Stewart argues that the stronger police presence has harmful impacts on minority communities. The increase in police presence would cause more young black men to be arrested on the basis of their skin color. This type of policing then leads to the extreme discrepancy in prison rates between blacks and whites. To Stewart, broken windows policing was a front for racist police officers. [17].

Despite the backlash against the practices of Broken Windows policing, the City of New York continues to use these practices up until today and defends their effectiveness. In 2014 Bill Bratton was brought back as the police commissioner in New York and, in 2015, released a report on the current state of policing. This report, entitled "Broken Windows is not Broken", is a response to a report by the Office of the Inspector General for the NYPD (OIG). The OIG report claimed that quality of life policing (the crack down on minor infractions), had no relation to the decrease in crime in New York City from 2010 to 2015. In his response, Bill Bratton argues that the OIG report had too narrow a focus and by examining the data closely, it could prove that active policing is responsible for the decline in crime [2]. The City of New York has not backed down from its adherence to broken windows theory and has endorsed it as recently as 2015.

2. Motivation

As a born and bred New Yorker, I have always been fascinated with Broken Windows policing and its effectiveness. As I was searching through the New York City Open Data database, I found a large history of crimes reported in New York City. I also found a database of parking tickets issues in New York City. I decided to see if I could use parking violations as a minor infraction in the framework of broken windows policing. The central question became: Are parking tickets and crimes correlated? If parking tickets and crime are negatively correlated, then we may be able to use parking tickets as a minor infraction to crack down on in the framework of broken windows policing. If the two variables are not negatively correlated, then this connection cannot be made and other conclusions should be reached.

In the process of doing this research I started looking into other relationships I could study. Are there certain months that crimes or tickets are more prevalent? Are parking tickets and crimes distributed equally across months? Are there certain days of the month that parking tickets are more common? Does weather have any impact on parking tickets issued? What about crime? These questions, along with many others, got answered by the time I was done with the project.

3. Related Work

3.1. NYC Parking

There have been many people who have studied the exact datasets that I analyzed. On Kaggle, a website designed for data analytics competitions, there was a competition to examine the parking dataset and answer these questions: When are tickets most likely issued? Any Seasonality? Where are tickets most commonly issued? What were the most common years and types of cars to be ticketed? Four different people created kernels and came up with some answers to these questions. They found that most tickets were given to people with New York license plates, noon was the most popular time of day tickets were issued, suburban cars were ticketed the most, and Ford, Toyota, and Honda were the brand of cars that were ticketed the most. These findings show that the dataset that I am working with has already been thoroughly dissected to understand trends in the world of parking in New York City [10].

A blogger named Ben Wellington has a website called iQuantNY, where he uses NYC Open Data to delve deeper into NYC issues. He has a series on parking tickets, where he studies the most blocked driveways in NYC. In addition, he created a mapping of travelers to New York through ticketed license plates [20]. One of his blogs was even used to prove that the city was improperly ticketing drivers in legal spots [7]. There have been many attempts to understand parking tickets in New York, but few in relation to crime.

3.2. NYC Crime

In addition to working with the parking dataset, many people have also studied the exact crime dataset that I was looking at. There was also a Kaggle thread for the crime dataset that had four contributors. These people studied the different relationship between the types of crimes that occurred and the location of occurrence. These results found that Brooklyn had the most overall crimes committed, but on a percentage or population basis, the Bronx and Manhattan had more incidents. The results also reflected that there are more crimes committed in the afternoon than late at night [9].

In addition, some students from NYU studied this dataset and "analyzed the top reported offenses for each of the five boroughs that form New York." This project aims to see where certain crimes in each borough are concentrated. They found that Petit Larceny was the most popular crime across all five boroughs, as well as no significant change in crime while the super bowl was in New York [16]. Just as with the parking research, we see that many people have used this dataset to find interesting results, but none relating the two.

3.3. Traffic Enforcement and Crime

None of the above research focused on the relationship between parking and crime. While few have researched the relationship between parking and crime, there have been many people that wanted to see how traffic enforcement could curb crime. In an opinion piece, Tom Vanderbilt argues that the more speeding tickets that are issued, the safer the world will be. He mentions that at least two of the 9/11 hijackers were stopped for speeding tickets [18]. This too can be seen in the framework of broken windows policing: giving more speeding tickets and increasing traffic stops will lead to less public disorder which will then lead to less crime.

The National Highway Safety Administration found that for a period of three years (1994-1996) after implementing a new policy, the change in overall traffic citations rose by 24 percent, while the number of violent and property crimes decreased by 10 and 12 percent, respectively [1]. This serves as an empirical example of how increasing traffic enforcement can cause a decrease in criminal behavior.

In his dissertation for Walden University, Marc Weiss studied the relationship between traffic violations and crimes. Throughout the study, Weiss references broken windows theory as the backbone of his research. He predicted that stopping more traffic violations would increase public order, which would decrease the amount of crime. In addition he anticipated that the increased presence of police officers on the roads would deter people from committing crimes. Weiss studied the relationship between crime and traffic violations in five counties in South Carolina. Weiss concluded with statistical confidence that there was a negative correlation between traffic enforcement and crime rates during a five-year period. He found that four out of five counties exhibited this negative correlation with confident enough p-values (at 5% confidence) [19]. This study was very similar to the study that I was conducting, except I analyzed parking tickets instead of traffic violations. In my research, I hoped to find similar results to the results Weiss found.

3.4. Weather and Crime

In her research, Ellen Cohn, criminologist at Florida International University, argues that temperature has a positive correlation with crime. That is, as the temperature rises, the rate at which crimes are committed increases too. Cohn's study focuses on trying to find a way predict crime better than traditional socio-demographic variables. The theory behind this reasoning is that humans typically like to follow routine. When the weather gets nicer out, more people alter their behavior and spend more time outdoors. This increases the number of people that are out and about, and thus increases the number of possible victims and perpetrators. In addition if more people are outside, there are more vacant homes, which leads to more burglary attempts. The underlying rational behind the study was proved to be correct when a positive trend between crime and temperature was found [4]. In my research I hope to find a similar correlation between crime and temperature. Cohn does not comment about the relationship between weather and parking tickets. It could be the case that as temperature increases, more people walk or use a bike so there are fewer cars to be ticketed. It could also be the case that when it is hotter, parking enforcement officers are more likely to be out and will give more tickets.

4. Approach

The main goal of this project is to understand the relationship between crime and parking tickets in New York City. In addition to understanding this relationship, I want to further understand how weather affects crime and tickets as well. The goal of my research is to build on the research done by Weiss examine whether parking tickets show the same negative correlation with crime as traffic violations do. Traffic violations are more expensive to enforce and are more dangerous to issue than parking tickets. To enforce traffic violations, you need more policemen out in the field pulling over cars. In Weiss' study, he found that "routine" traffic stops often became violent and were a direct threat to the officer's lives. Parking tickets, on the other hand, rarely end in violence, so are a safer and cheaper alternative. Thus, if I find similar results to those of Weiss, I have found a cheaper and safer way to halt crime than enforcing traffic violations. For these reasons, I decided to study parking tickets to see how they relate to crimes. In the process of this research, I also studied the relationship between the day of the month and chance of crime or parking tickets to see if there were any inconsistencies in the data. Finally, I looked at how weather affected these two variables. After finding a relationship between crimes and parking tickets, I additionally wanted to understand more about how outside factors affect these two variables. The conclusions about weather and day of the month may reinforce some of the correlations between crime and parking. If crime and tickets issued both rise as temperature rises, then a correlation in the variables may just be due to temperature.

5. Implementation

My implementtion can be broken down into four phases. I first needed to collect the data, then clean the data, then plot and run regressions, and finally apply this method to the weather data.

5.1. Data Collection

All of the Parking Data that I analyzed was available on NYC Open Data (a website run by NYC government that releases data to the public for free). For the parking tickets, I download the csv files for all parking tickets issued. The parking data was segmented into 4 different files. The files for the years 2017, 2016, and 2015 all had the same format (by calendar year), so downloading the csv was straightforward. The data for 2014 was organized by fiscal year, so it ran from August 2013 to June 2014 [6]. The csv was downloaded the same way, but the difference in calendar year versus fiscal year brought about some processing issues.

The next dataset I collected was also from NYC Open Data. At first I downloaded a file that contained aggregate crime information by year, but realized that yearly cumulates were not granular enough. In order to study the temporal relationship between parking and crime, the yearly totals would not be enough: I needed the information on a monthly or daily basis. After searching on the website, I found a download that contained all NYC crimes by the day they were reported from 2006 to 2016 [5]. This file was not as easy to download as a csv file because some of the types of crimes contained commas in them. This caused an issue in the data parsing, so I decided to download the data as a tsv instead. This solved the parsing issues I was having with the csv files.

For the third dataset, I sought to obtain weather data for New York City for the three year period I was studying. I went on Weather Underground to get historic weather data. I chose Central Park, NY as my location as it is central in the five boroughs and the weather in Central Park will not be so much different from any part of the other boroughs. I was only able to collect one year at a time, so I split the data into three queries and then put them together into one csv file. Now I had all the data I needed in a format that I could then analyze.

5.2. Data Cleaning

Once I had this data I needed to read it into a usable format. In order to do this I used a Python Jupyter notebook and read in the data. I only read in the columns that were necessary, such as the date and time each event happened, the precinct in which the event occurred, and the type of crime (for the cries dataset). There were some special cases where dates needed to be parsed properly upon conversion. I read all the files into Pandas Dataframes. I felt that this type of structure would be easiest to manage. I had never worked with Pandas before, but it was similar to manipulating an excel file so I felt comfortable using it. The first thing I needed to do was combine all the parking data into one Dataframe after reading it in from 4 different csv files. The parking data was from august 2013 - 2017. The crime data was from 2006 to 2016. I needed to trim both datasets so that I only captured data from 2013 - 2016. After trimming, both datasets lined up.

Next, I needed a way to deal with errors in the dataset. I decided that something was classified as an error if the precinct that was reported was not in the array of accepted precincts. This classification eliminated some of the data but it was a small proportion of the total (around 1 percent of the total data). Next, I grouped all of the data by month. I did this using the Pandas groupby function. This gave me the ability to see the data in a cleaner, more concise way. I also was able to group the data by day and by week in order to plot and find irregularities in the data.

The next part of data cleaning was to group the data by precinct. This step was also helpful later on to be able to see the data on a precinct-by-precinct basis. I then was able to sort the precinct data by which borough they belonged. I was also able to categorize the data by type of crime (violation vs. misdemeanor vs. felony). After doing this cleaning I had the data in a clean form that allowed me to perform the desired regressions and tests.

5.3. Plot Data and Running Regression

The first question I wanted to answer was to try to find a correlation between total parking tickets in all five boroughs and total crime in the area. To do so, I grouped both by month and then plotted them side-by-side on a bar graph. Plotting this data was not as easy as expected because there were issues labeling the axis correctly. The x-axis was supposed to be a date, but I had issues converting each of the date objects to datetimes so that the dates on the axis would show up correctly.

The results looked as if parking and tickets were correlated so I then plotted each variable against the other and ran a regression on the data. I used scipy's linregress function, which uses a least-squares regression on the data. This was an appropriate regression to run because I was looking to find a linear correlation in the data and least-squares would serve this goal well. This package runs the regression and then prints out the slope, intercept, r-value, p-value, and stderr. I was most interested in the r-value's and the p-value's as this would show if there was a correlation and what type of correlation there would be. I was then able to graph these two variables against each other with the line of regression on the same plot to see how the line fit the data.

After seeing how the data fit, I ran the same script but grouped the data by precinct and by borough. This would give a clear picture as to how different precincts and boroughs performed against each other. This grouping would also show if the same correlations existed on smaller samples as they did on the larger one.

5.4. Analyze Weather Data

Once I finished analyzing the correlation between crime and parking tickets, I decided that it would be significant to look at the impact of weather on parking tickets and crime. I gathered the data from weather underground and did minimal cleaning just to ensure the dates lined up. I studied temperature, humidity, and precipitation. I first needed to group the data by day and see how many days in the year each of these phenomena happened. I decided to group days in a range so instead of plotting the average of all days where the temperature was 50 degrees, I plotted all days where temperature was between 50 and 55 degrees. This was a more effective way of showing the data and took out many outliers where one day had a larger affect on the total. I did the same grouping for humidity and precipitation. When plotting this data, I decided to shave off a bit from the upper and lower range from each of the three features. I cut out all groups that had less than 5 days in the year fall in that range. This cut out many outliers as well and gave a more reliable representation of the data.

6. Results

6.1. Initial (Parking vs. Crime)

Originally, I plotted a bar graph of the tickets and crimes by month over the time period that I was studying. I did this so I could quickly visualize the results and try to spot any trends. From the looks of it, crime and parking tickets generally followed each other except for a large discrepancy in January 2015 (Figure 1, Appendix Figure 8). I thought this was significant and took note of it.

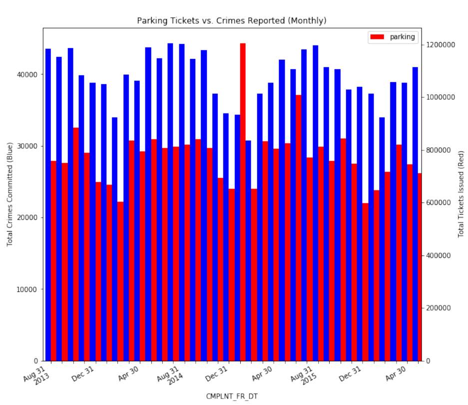

Figure 1: Crimes and tickets per month

Figure 2: Crimes vs. parking with regression

I then plotted parking vs. crime on the same graph and ran a regression on the data. In this regression, I saw a pretty accurate line of best fit, except for one large outlier. I circled this outlier on the graph and realized that it was the point for January 2015 (Figure 2, Appendix Figure 9). The results from the regression were pretty good with a reported: r-value = .509, and p-value = 0.139. This regression was a good start and showed that there was an initial positive correlation between crime and parking tickets. I decided to further investigate why January 2015 was such an anomaly in the data.

6.2. Abnormal Data

In the quest to understand January 2015, I found a very fascinating story about the events in New York city during that month. On Decemeber 20^{th}, 2014, two police officers were shot dead in their car in Bedford-Stuyvesant, Brooklyn. In a Facebook post, the gunman claimed that this was a response to the deaths of Eric Garner and Michael Brown [14]. As a result of the murder of these two policemen, many policemen felt that the mayor was not protecting them and turned their back on Mayor Bill de Blasio, ans refused to do their jobs. In the days from December 20^{th} to January 6^{th}, New York City saw a 55% drop in arrests and a 92% drop in parking tickets issued [15]. These tickets are a large revenue source for the city and if cut short would stifle their budget. On January 6^{th} Mayor de Blasio made a speech saying that he was investigating the slowdown and would bring New York's finest back to work [13].

In the weeks after the speech by the mayor there was an unprecedented rise in parking tickets issued. The mayor's office put pressure on the city's employees to do their jobs. We can see from the graph below that between December 20^{th} and January 6^{th}, there were very few tickets issued, but after January 6^{th} the number of tickets issued skyrocketed (Figure 3). This data was such an anomaly that throughout the three years there were 23 days in which parking tickets exceeded 40,000. Of these 23, 16 occurred in the month of January 2015.

I found that this was sufficient evidence to label the months of December 2014 and January 2015 as irregular data and I omitted them from the remaining calculations.

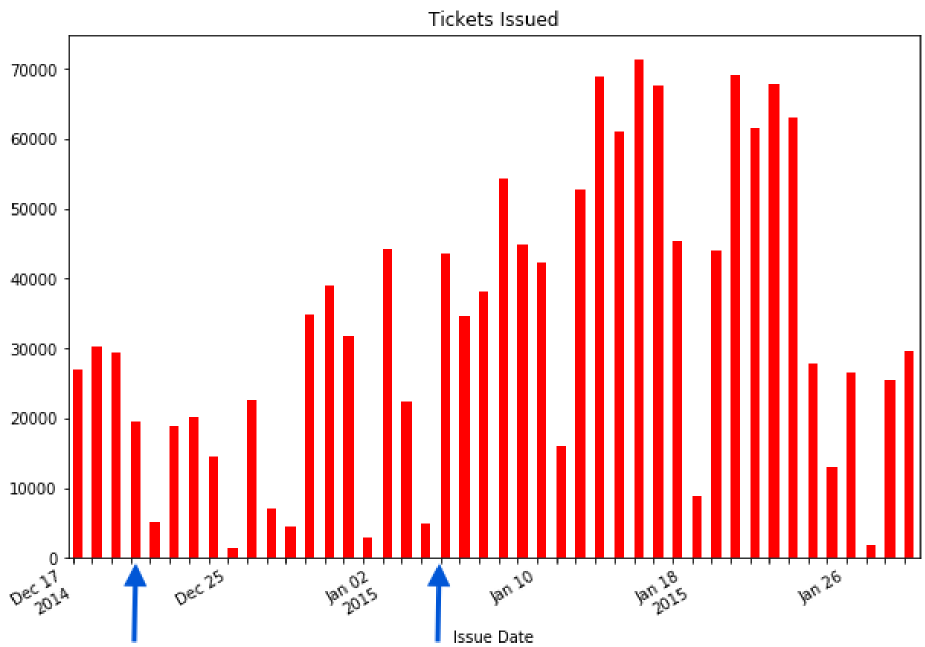

Figure 3: Tickets issued in Dec. '14 and Jan. '15 with arrows pointing to Dec. 20 and Jan. 6

6.3. Second Test (Parking vs. Crime)

Now that I omitted the data from December 2014 and January 2015, I ran the regression again to see what the results would be without these two abnormal months in the dataset. When looking at the bar graph I saw that the bar for parking tickets did follow the par for crimes. Look at the regression, there is an r-value = .578 and p-value = 0.000525. This p-value is statistically very small and shows that it is extremely unlikely that this correlation would happen by random chance. The r-value shows that there is a positive correlation between the two variables (Appendix Figures 10 and 11). This correlation shows that crime and parking tickets are strongly positively correlated, contrary to my initial claim.

6.4. Borough Breakdown

When plotting the data for each borough, all five boroughs show this positive correlation (Table 1). Each of these values can be accepted with $\alpha = 5\%$ confidence and all boroughs besides Staten Island can be accepted with a $\alpha = 1\%$ confidence level. This breakdown of the data into 5 boroughs is similar to what Weiss did in his breakdown into 5 counties of South Carolina. In his case, he found that four out of five of his counties showed significant negative correlation between traffic violations and crime. In my case, I can conclude that across all five boroughs there is a significant positive correlation between parking tickets and crime.

Borough	R-value	P-value
Manhattan	0.522	0.002
Brooklyn	0.477	0.006
Bronx	0.485	0.005
Queens	0.521	0.002
Staten Island	0.35	0.049

Table 1: Top 5 Positive Correlations

6.5. Precinct Breakdown

The next research I conducted was to see if I could break down the information to see if the above trends persisted on a precinct level. A full view of how the precincts performed can be found in the Appendix in Tables 5, 6, 7, 8, and 9. Below I listed the top five precincts that showed the largest correlation between parking and crime (Table 2). All of these show strong positive correlations with low p-values. When we look at the bottom five correlations (Table 3), two out of five are small negative correlations, while the other three are very small positive correlations. These "low" performing precincts all have large p-values, which shows that the data can be largely due to random chance. From this I can conclude no precinct has a strong negative correlation between tickets and crime, while there are many precincts that have strong positive correlations.

Precinct	R-value	P-value
60	0.805	$2.88 * 10^{-8}$
100	0.748	$2.76 * 10^{-7}$
113	0.576	0.001
26	0.563	0.001
40	0.547	0.001

Table 2: Top 5 Positive Correlations

Precinct	R-value	P-value
111	-0.088	0.631
61	-0.008	0.966
17	0.027	0.882
105	0.037	0.841
79	0.072	0.696

Table 3: Bottom 5 Correlations

6.6. Third Test (Parking vs. Type of Crime)

It was not enough to only examine the total crime and the difference amongst the various precincts. The next tests I ran were on different types of crime to find out which were the most correlated to parking tickets. The dataset broke down the crimes into misdemeanors, violations, and felonies. Using the graphs (Appendix Figures 12, 13, and 14) and corresponding r and p values (Table 4), we see that misdemeanors are the most positively correlated, followed by violations, followed by felonies as the least correlated. Here we see that the more severe the crime the less correlated it is with the amount of tickets that were issued. We also see from the p-values that the positive correlations between tickets and each of these crimes will be accepted with $\alpha = 5\%$ confidence. From here we see that as the crimes get more violent, the less correlated they are with parking tickets. This trend should make intuitive sense because some may label a parking ticket as a very minor crime, so it should be closely related to other minor crimes.

Type of Crime	R-value	P-value
Misdemeanor	0.610	0.0002
Violation	0.548	0.0012
Felony	0.400	0.0231

Table 4: Types of Crimes

6.7. Weather

After looking into the correlation between crime and tickets, I decided to look at the impact of weather on these variables. I broke down the weather data into temperature, precipitation, and humidity.

6.7.1. Temperature: When looking at the temperature, it is reasonable to assume that the crime data in New York is very similar to Ellen Cohn's trends found in Chicago. As mentioned earlier, Cohn found that as temperature increases, more people venture outside, which leads to more crimes being committed. When looking at the data the same trend was found to be true for crime (Figure 5). When looking at the parking data I prdicted that as the weather became extreme – really hot in the summer or frigid in the winter – less parking tickets would be issued because officers would not want to be outside in that weather. When looking at the data, the results determined otherwise. The plot of parking versus temperature shows that as temperature increases, the number of parking tickets issued stays the same (Figure 4).

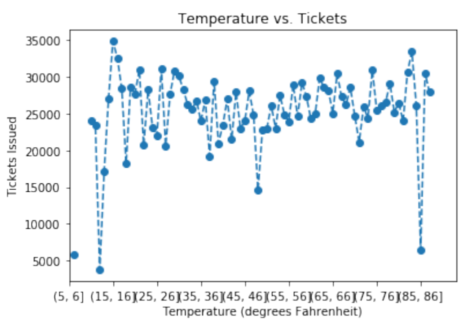

Figure 4: Tickets by Temperature

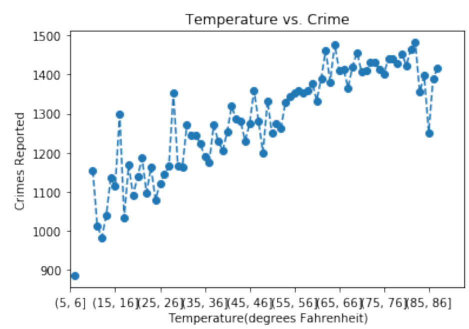

Figure 5: Crimes by Temperature

6.7.2. Humidity: I then looked at how humidity affects tickets and crime. When humidity is very high this usually means that it is raining out. The graphs show that as humidity increases, crimes and parking both decrease. This trend seems to back up the standard intuition that officers do not go out in the rain, but it also brings up questions as to why less crimes are reported in the rain (Figures 15 and 16).

6.7.3. Precipitation: The precipitation data shows similar trends to the humidity data (as the two are related). In this case as precipitation increases, both crimes and tickets decrease. This trend again is interesting in the relationship between rain and crime (Figures 17 and 18).

6.8. Day of Month

Lastly, I wanted to examine whether there was any relationship between the day of the month and the chance a parking ticket is issued. I remembered hearing growing up that I should be extra careful at the end of the month because the meter maids needed to fill their unofficial ticket quotas for the month. I would also assume that crime would not have anything to do with day of the month: Why would a criminal not commit a crime because it is a certain day of the month? At first glance, the plots of the data seem to show that there are slightly more tickets issued at the beginning of the month. This looks significant, but with deeper analysis, we see that the indices are very small, so the difference between day 1 and the rest of the days could be due to general noise (Figures 6 and 7). This similar trend also exists in the crime data; however, it does not make sense that more crimes would be committed on the first of the month more than any other day. The axis on the crime graph is even smaller and shows that the increase in the first of the month is just noise as well. Because of these observations, I conclude that there is no correlation between the day of the month and both crime and parking.

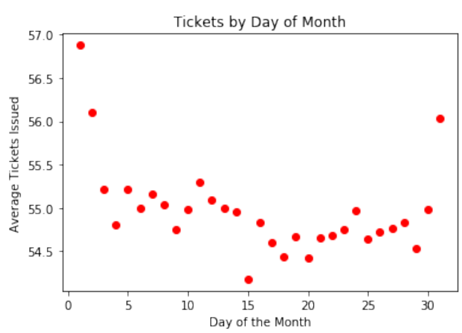

Figure 6: Tickets by Day of the Month

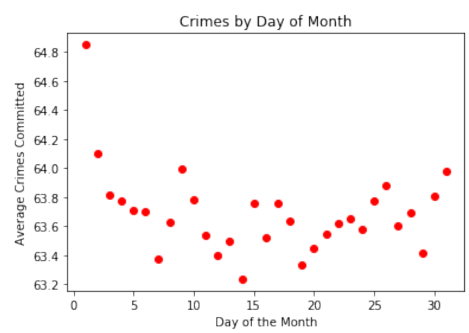

Figure 7: Crimes by Day of the Month

7. Conclusion

As a result of the research done throughout the semester, I have discovered several conclusions about weather, parking tickets, and crime, and how they all are related.

7.1. Parking vs. Crime

At the start of this research I set out to answer one critical question: Can parking tickets be seen as a minor crime in the framework of broken windows theory? Does the increase in parking tickets yield a decrease in overall crime? What I ended up finding is that parking tickets actually have a strong POSITIVE correlation with crime, denoting that an increase in parking tickets would yield an increase in crime. This data comes in direct contrast to the study done by Weiss on traffic violations and the negative correlation between stopping motorists and overall crime. I would conclude that this project was a success in the goal of finding an answer to a thought-provoking problem. I set out to truly understand the relationship between parking and crime and I have come out with a clearer picture of how these two are interrelated.

7.2. Weather

During the process I became interested in how relates to the variables I was studying. The main impetus for this probing was what seemed to be a cycle where more crimes and parking tickets occurred in hotter months and colder months. After looking closer at the data and plotting these relationships, I found that crimes do increase as temperature increases, but temperature has no effect on parking tickets. I also found that precipitation and humidity both have negative effects on parking tickets and crime. This seems to make logical sense, as officers would not want to give tickets in the rain.

7.3. Day of Month

The last piece of evidence that I investigated was how likely one is to get a ticket or commit a crime depending on what day of the month it was. In the end I found that there was no relation between the day of the month and the probability of getting a ticket or of committing a crime. This alone is noteworthy because it can inform the general public that the day of the month should not weigh into their decision to pay the meter or not.

8. Further Research

If I were given another semester on the project, there are many things that I would want to fully investigate. I would visually graph how the precincts compare to the average. I would have liked to do this for this project but the time constraint did not allow for it. The next major thing I would look at would be to see if I could find similar data for other cities and see if this same correlation still holds. Maybe there is something special about New York that there is this positive correlation between crime and parking tickets but in other places this may not be the case? Maybe the sample I had (3 years) was not enough data to make full conclusions. Maybe some of the weather conclusions I made were not accurate because of the small sample size and different trends will arise if looking at a larger timescale? I would love to explore all of these options to see how far I can extend this research and to see how widespread these correlations are, or if my research dataset was just a fluke. Because of this positive correlation I found, I would attempt to build a predictive model that uses parking and other data to predict the amount of crime that will occur in a particular area.

9. Ackowledgements

I would like to thank my advisor David Dobkin and my seminar classmates who helped me turn my original idea into a reality. I would like to thank Rachel Linfield for helping edit this paper. I would also like to thank my parents for their constant love and support.

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10. Appendix

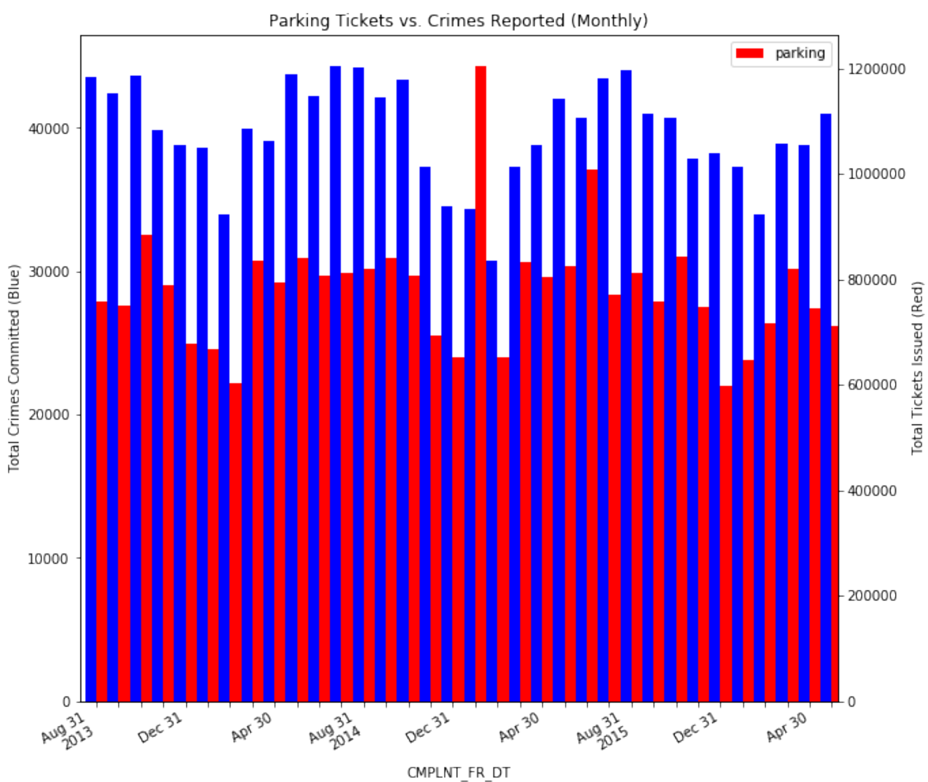

Figure 8: Total tickets and crimes by month

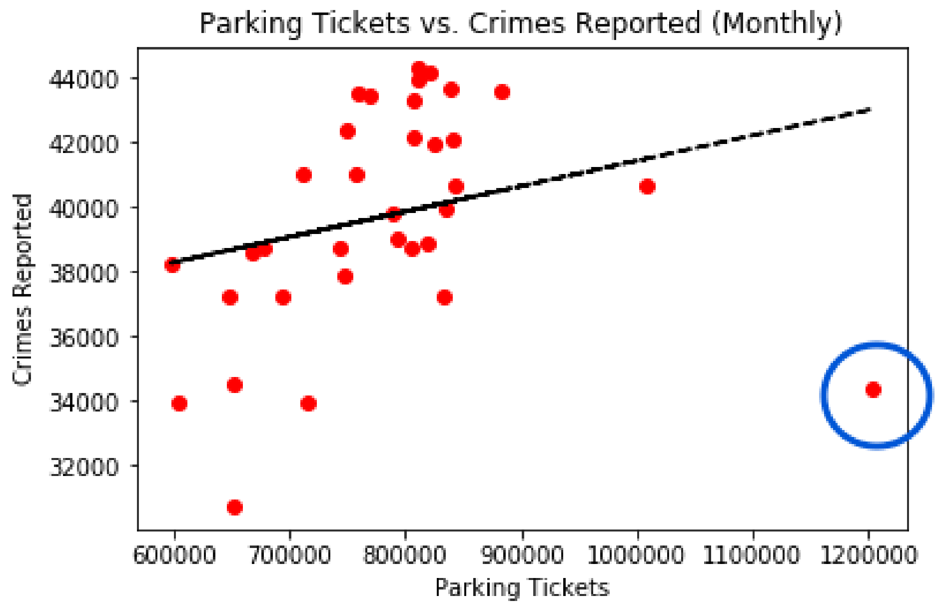

Figure 9: Tickets vs. crimes plus regression with Jan. 2015 circled

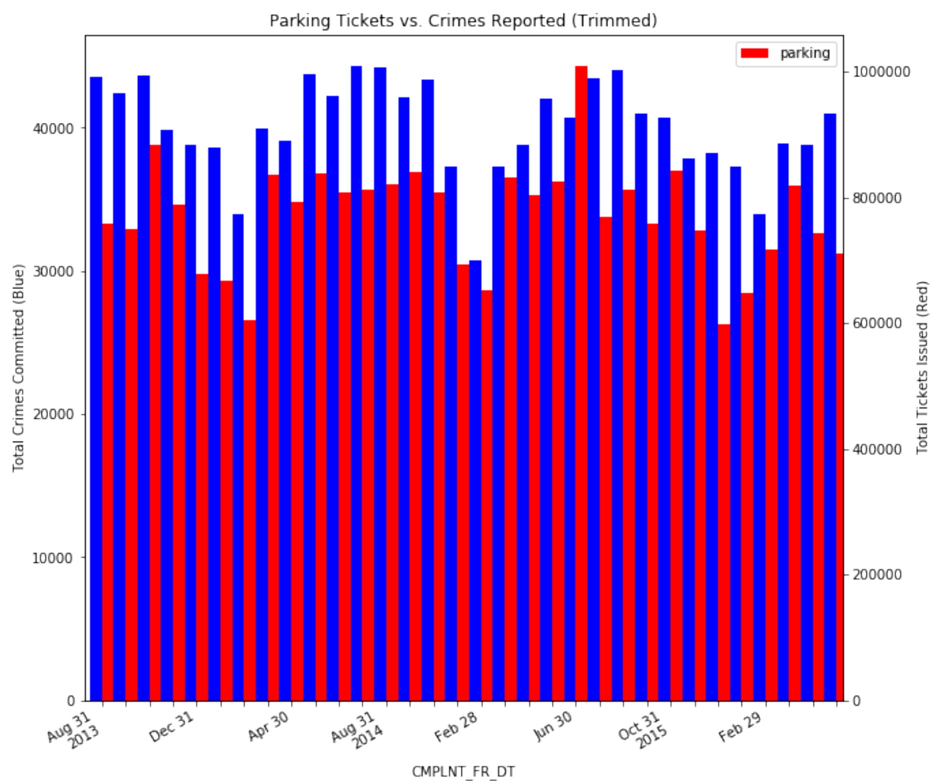

Figure 10: Total tickets and crimes by month (trimmed)

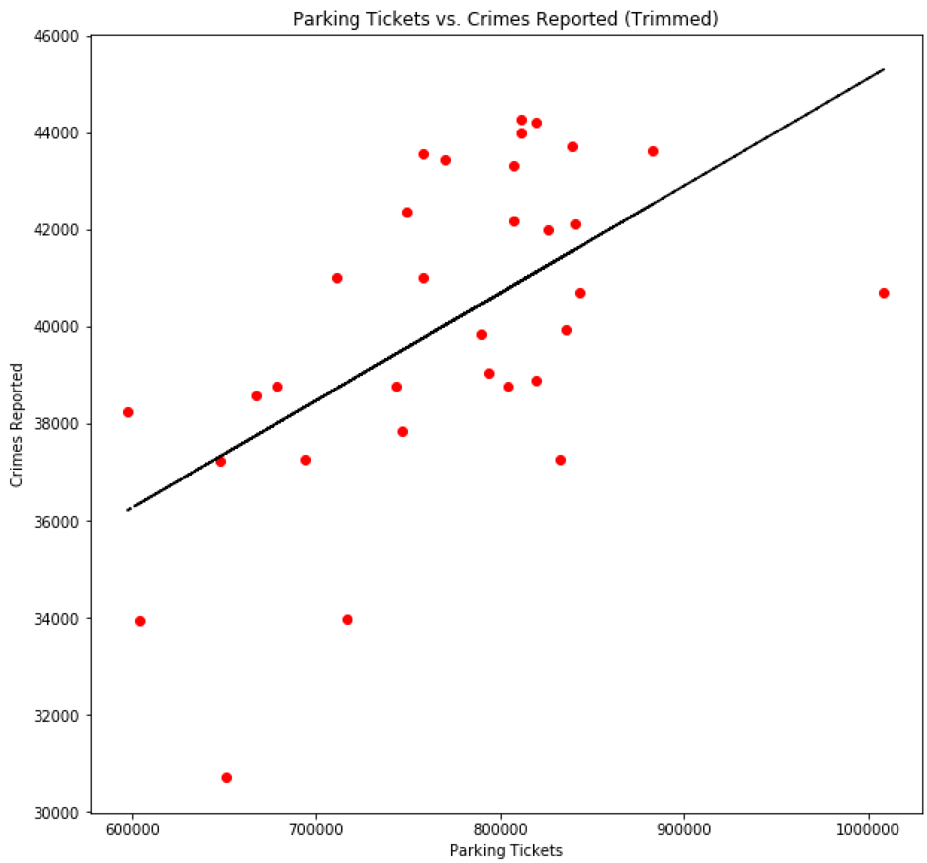

Figure 11: Tickets vs. crimes (trimmed)

Precinct	R-value	P-value
1	0.153	0.402
5	0.243	0.18
6	0.46	0.008
7	0.294	0.103
9	0.356	0.046
10	0.311	0.083
13	0.249	0.169
14	0.221	0.224
17	0.027	0.882
18	0.081	0.661
19	0.172	0.347
20	0.542	0.001
23	0.434	0.013
24	0.465	0.007
25	0.535	0.002
26	0.563	0.001
28	0.395	0.025
30	0.135	0.461
32	0.39	0.027
33	0.321	0.073
34	0.263	0.145

Table 5: Manahttan Precincts

Precinct	R-value	P-value
40	0.547	0.001
41	0.134	0.465
42	0.123	0.504
43	0.079	0.667
44	0.43	0.014
45	0.305	0.09
46	0.35	0.049
47	0.451	0.01
48	0.229	0.208
49	0.271	0.133
50	0.279	0.122
52	0.339	0.058

Table 6: Bronx Precincts

Precinct	R-value	P-value
60	0.805	$8.22 * 10^{-8}$
61	-0.008	0.966
62	0.468	0.007
63	0.325	0.07
66	0.112	0.541
67	0.175	0.337
68	0.502	0.003
69	0.204	0.262
70	0.244	0.178
71	0.249	0.169
72	0.111	0.544
73	0.29	0.108
75	0.469	0.007
76	0.369	0.038
77	0.134	0.465
78	0.534	0.002
79	0.072	0.696
81	0.229	0.207
83	0.281	0.12
84	0.539	0.001
88	0.333	0.063
90	0.219	0.229
94	0.529	0.002

Table 7: Brooklyn Precincts

Precinct	R-value	P-value
100	0.748	$8.76 * 10^{-7}$
101	0.356	0.045
102	0.405	0.022
103	0.481	0.005
104	0.499	0.004
105	0.037	0.841
106	0.159	0.385
107	0.366	0.039
108	0.397	0.024
109	0.487	0.005
110	0.378	0.033
111	-0.088	0.631
112	0.19	0.298
113	0.576	0.001
114	0.382	0.031
115	0.092	0.615

Table 8: Queens Precincts

Precinct	R-value	P-value
120	0.247	0.173
121	0.309	0.085
122	0.229	0.208
123	0.478	0.006

Table 9: Staten Island Precincts

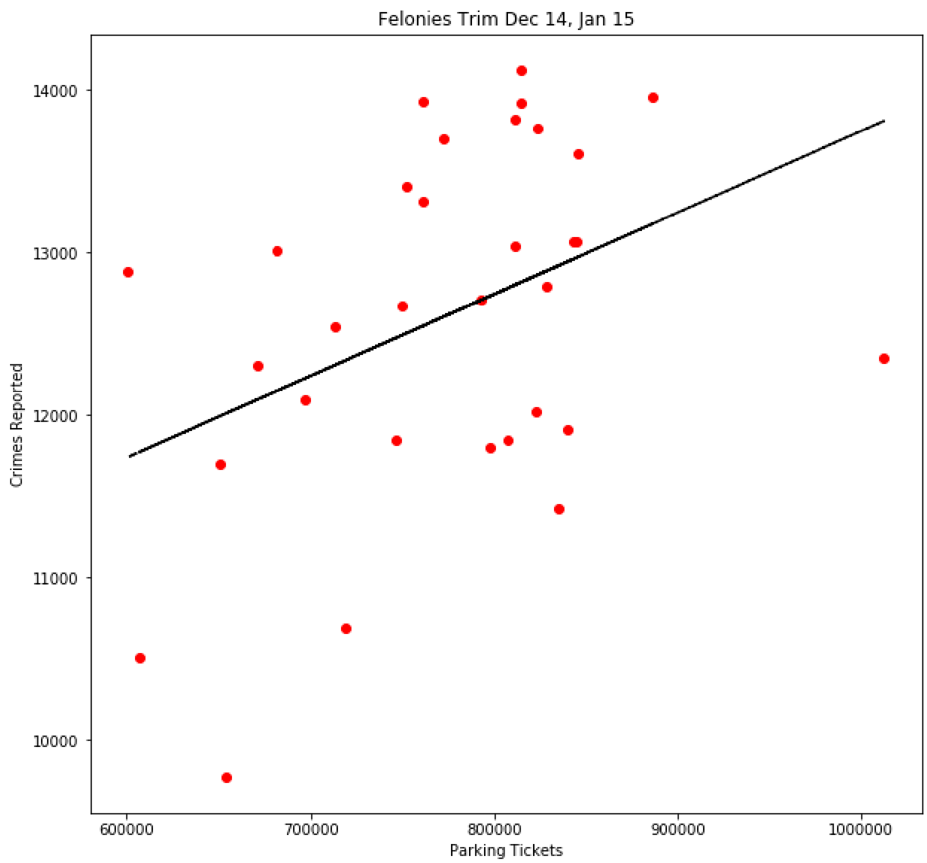

Figure 12: Tickets vs. Felonies

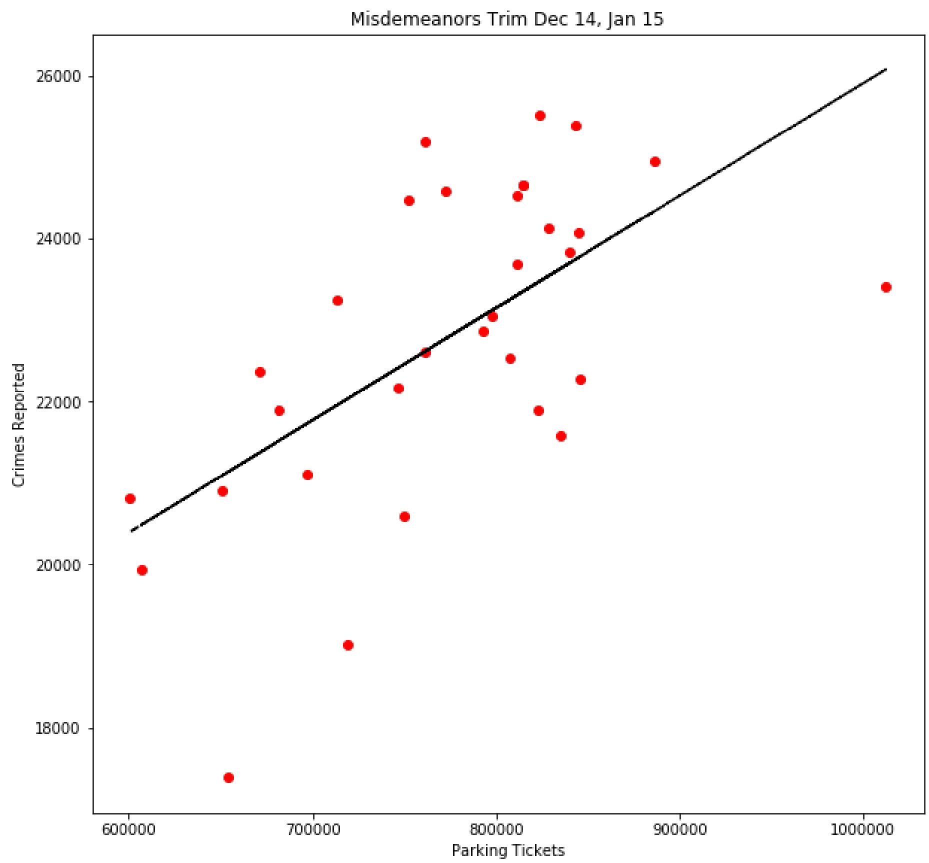

Figure 13: Tickets vs. Misdemeanors

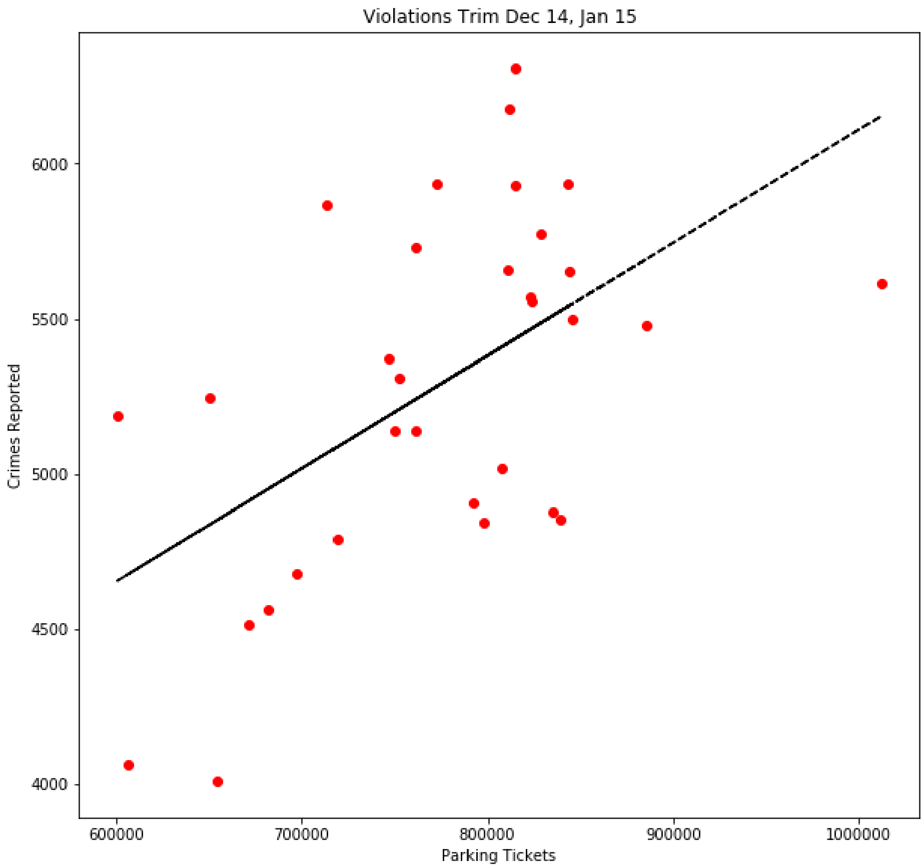

Figure 14: Tickets vs. Violations

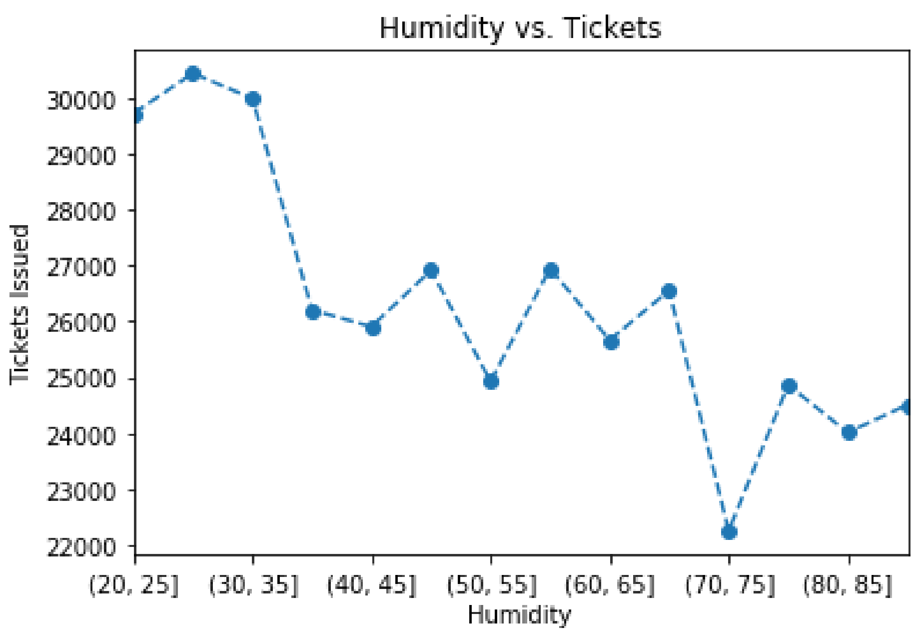

Figure 15: Tickets by Humidity

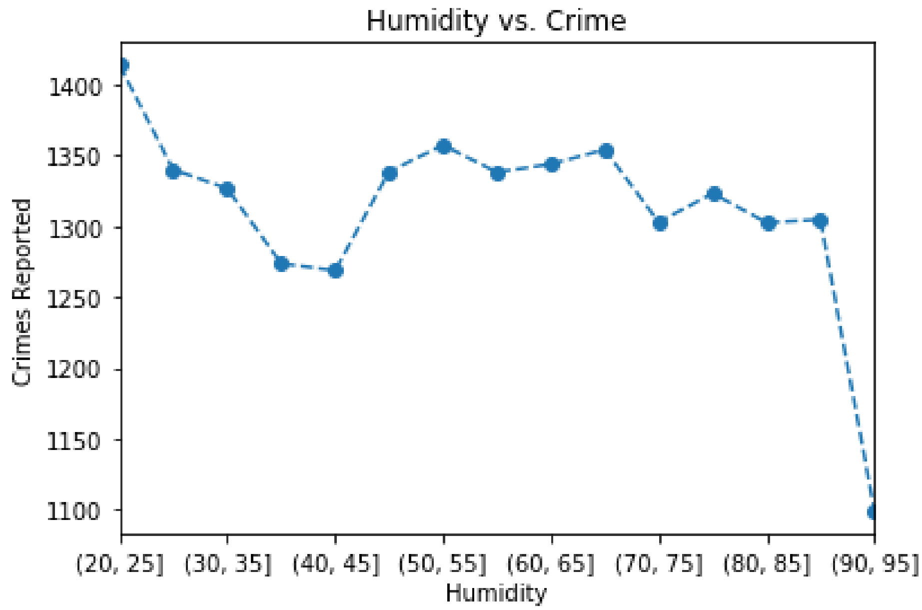

Figure 16: Crime by Humidity

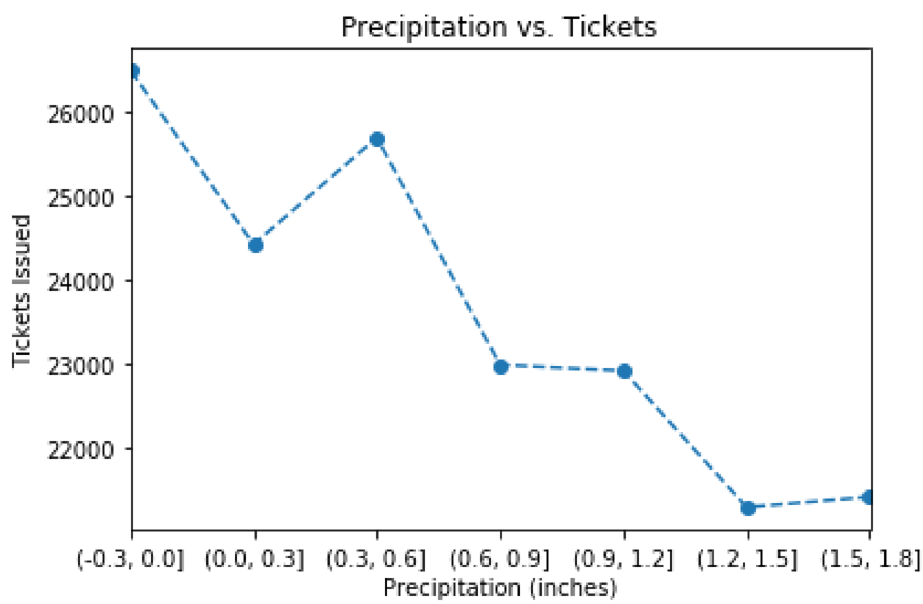

Figure 17: Tickets by Precipitation

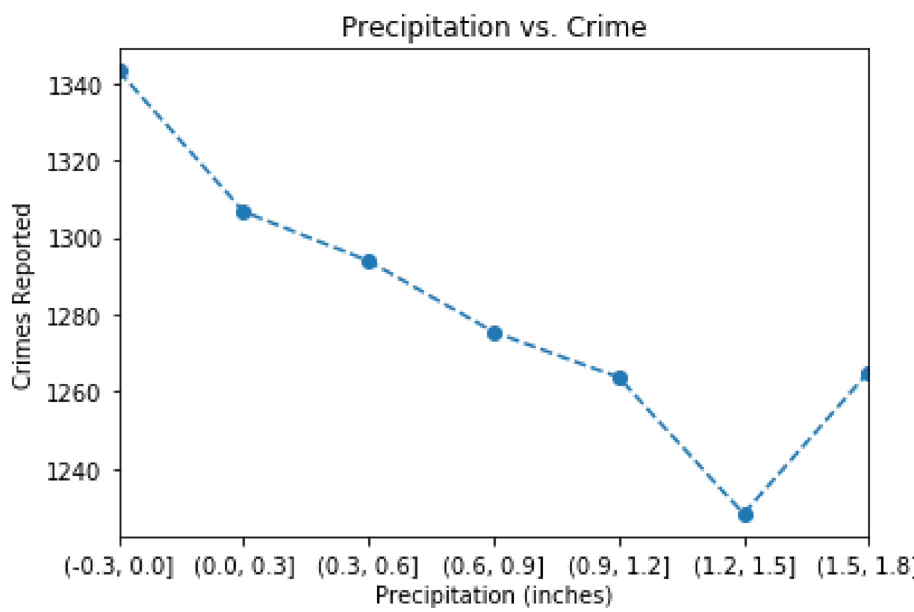

Figure 18: Crime by Precipitation