For office use only
T1 _____
T2 _____
T3 _____
T4 _____

For office use only
F1 _____
F2 _____
F3 _____
F4 _____

2015

18th Annual High School Mathematical Contest in Modeling (HiMCM) Summary Sheet
(Please attach a copy of this page to each copy of your Solution Paper.)

Team Control Number: 6018

Problem Chose: B

Our model serves to describe the safety of My City with a rating that can be compared to the FBI Crime Data for cities and metropolitan areas. The FBI data was approximated to represent a normal distribution, and because the My City data fit the normal distribution, the model was able to rate My City in relation to the cities and metropolitan areas within the United States. The model that was used to best represent that safety ranking was $R_m = \Sigma(W_c \times C_m)$ in which R_m was the rating of the metropolitan area and was calculated with the summation of each of the major crime's rate per 100,000 people for two weeks multiplied by its individual weights. The weights were calculated by the sentence of each crime using data from the United States Sentencing Commission by using the median sentence given for each crime used in the safety ranking.

The advantage to this rating system is that it incorporates the frequency of crime occurrences as well as the severity of the crime into the safety rating. The calculated safety rating for My City was 1370.9268 and the mean of the FBI metropolitan area ratings was 1462.467 with a standard deviation of 564.8396. As a result, the z-score of My City in relation to the population of FBI data was -0.1620636, meaning that it was safer than 56.43 percent of cities.

In addition to this, a city that was most similar to My City was found based on the safety rankings and population size and was determined to be Chicago. Using GDP and crime data for several years in Chicago's past, a significant correlation was determined between the crime rate and the GDP of Chicago, which was then concluded to also apply to My City due to their similarities.

Also, using a model to determine which of the district and beats had the most dangerous proportion of violent and property crime within My City, district-specific values were established that represented the proportion of the My City police force that would be assigned to each district in order to optimize the the safety by placing more officers in more dangerous districts and fewer in less dangerous ones.

Restatement of Problem

Crimes in the United States of America have been recorded since the birth of the country. And with such ample amounts of detailed criminal records collected by organizations like the Federal Bureau of Investigation and the National Crime Victimization Surveys, a massive database of crime statistics has been accumulated over the years—especially statistics within major cities. Thus, this paper aims to analyze such criminal data for a specific city and determine the city's safeness via a developed rating method. In addition, the paper will correlate the city's number of reported crimes to the economic activity and examine the placement of additional law enforcement within My City to improve the city's safeness.

Introduction

In October of 2002, two men brought fear in the hearts of Americans as they claimed the lives of ten innocent bystanders and critically injured three others over a period of twenty-three days. These heinous crimes instilled terror in the citizens living in the Maryland, Virginia, and Washington D.C. area.[1] People in this region were afraid of leaving their homes. Schools and businesses were closed until the men behind the murders were brought to justice. Eventually, both of the snipers were brought to justice. However, the crime was not forgotten.

For years, criminal activity has been a major issue in the United States of America. In the 2015 mid-year report, the US was ranked 45th out of 120 countries in terms of its crime index.[2] In 2002, data showed that we were ranked first out of 82 countries for our number of total crimes. During this year, there was a total of 11.88 million cases accounted for—a value that surpassed the second ranked country, the United Kingdom, by almost double the crime count.[3] In 2012, the United States law enforcement also made over 12 million arrests

nationwide. Of these arrests, 4.273%, or 521,196 cases, were due to violent crimes.[4] The statistics go on and on.

Such extensive data on crime, therefore, is critical for the evaluation of a nation's criminal activity. It not only shows the numerical value for crimes but also the trend in data. For example, in 2013, the number of estimated arrests was 11,302,102—a 7.3367% decrease from 2012.[5] This drop coincides with the overall decreasing trend in reported crimes in the United States since the early 1990s as shown in Graph 1 of Appendix A regarding the total number of reported crimes over time.

This annually compiled data provides massive statistics. Within the United States, this data is collected by a myriad of organizations, one of which is the Federal Bureau of Investigation (FBI). For the FBI, the Uniform Crime Reporting (UCR) program is used. This program gathers information regarding only violent crime (categorized by murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault) and property crime (categorized by burglaries, larceny-theft, and motor vehicle theft), and data using this system has existed since 1930.[6]

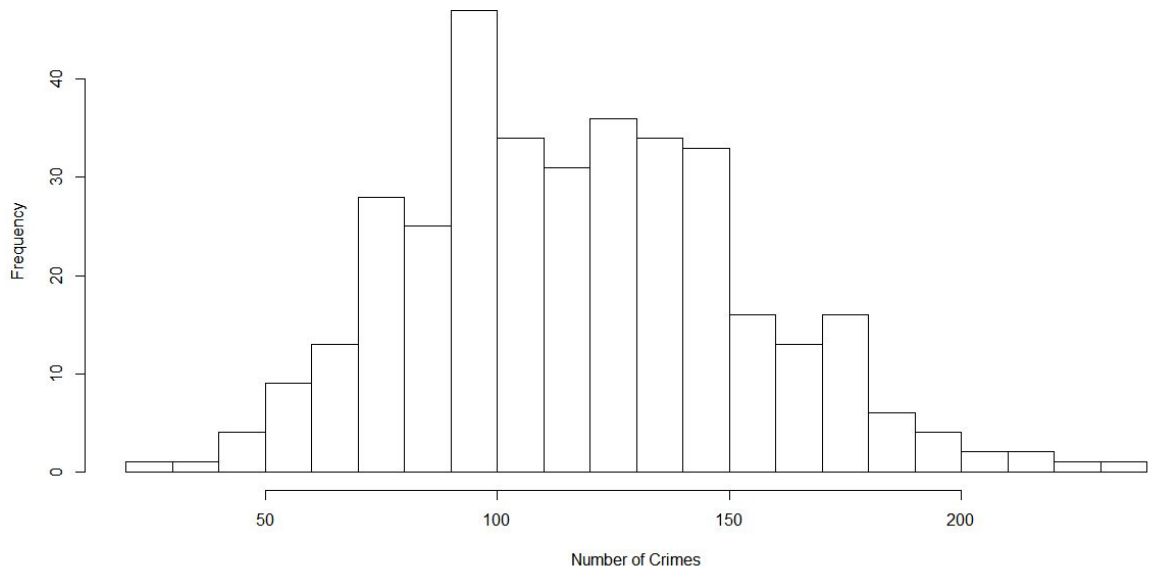
This paper thus seeks to apply the abundant amount of gathered criminal statistics to the safeness of cities and metropolitan areas. Data regarding crime reports will be analyzed in order to develop a system for rating an area's safeness. Furthermore, a correlation between the criminal activity and the location's economic prosperity will be explored as well as the placement of additional law enforcement in order to improve a city's safeness rating.

Global Assumptions

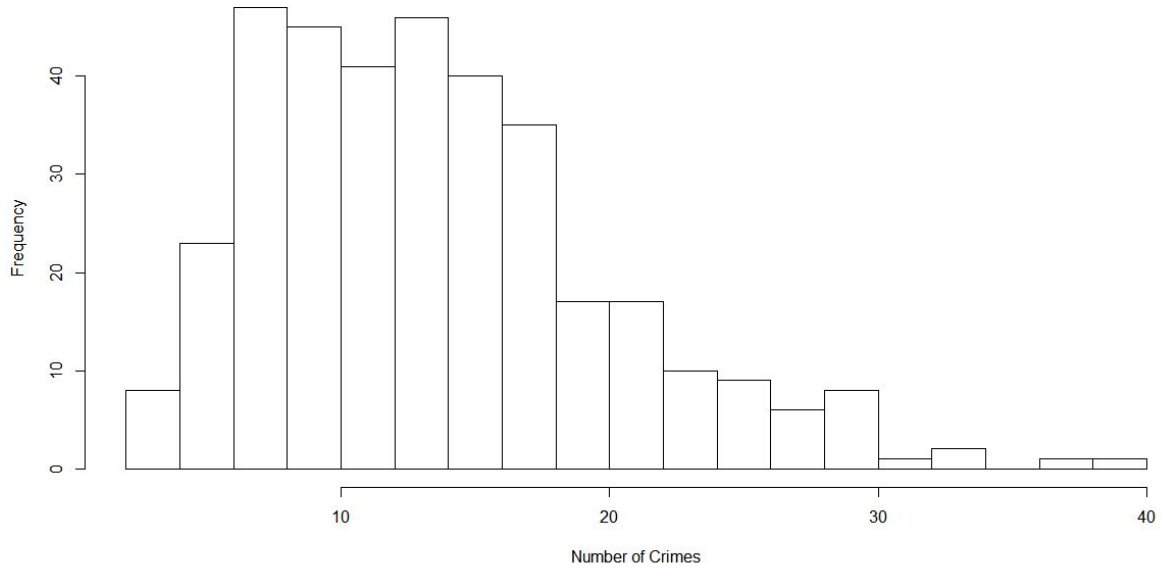
To adequately analyze the criminal data, several assumptions were developed. These included:

1. My City is a city in the United States of America.
    - Thus, FBI reported data can be applied to the problem.
2. My City, which has a population of 2.8 million people, is impacted by a metropolitan area of an additional approximately 6 million people.
    - Due to this, the reported crimes of My City are affected by the 6 million people of the metropolitan area, also. And thus, the value used for total population influencing the crime data set is 8.8 million rather than just the 2.8 million of My City.
3. The My City crimes given are the only crimes that occurred in My City and its metropolitan area.
4. The crimes that occur are distributed uniformly across the year.
    - Thus, when the annual distribution of FBI's metropolitan crime data is used, the data's yearly values can be divided by 26 to obtain the data collected over just a two week period (the time frame of collected data in the My_City_Crime_Data.xlsx file).
5. Since the distribution of frequency of metropolitan areas' number of crimes is approximately normal (see graph below), data could be standardized.
    - The FBI uses the UCR program, which incorporates the Hierarchy Rule.

Graph 2: Number of Crimes per 100000 per Two Weeks under Hierarchy Rule



Graph 3: Number of Violent Crimes per 100000 per Two Weeks under Hierarchy Rule



Model 1

The purpose of Model 1 was to determine a method for rating the safeness of My City as well as My City's metropolitan area (from here on, any mentioning of "My City" will thus refer to My City and its metropolitan area). The given crime data for My City included a

variety of information, such as the date of occurrence, primary and secondary descriptions, location description, arrest, domesticity, and beat number. However, for the formulated method of rating, the primary and secondary descriptions of the crime where most significant.

The recorded crimes were first categorized by their primary description and further sorted by their secondary descriptions. The frequency of each crime was then counted. In order to develop the ranking system (based on z-score calculations), however, the crimes must further be categorized into "violent crimes" and "other crimes." The definitions of violent crimes and other crimes are found in Assumptions for Model 1.

Assumptions for Model 1

1. "Violent crimes" were defined as any crime in which the perpetrator's actions can result in potentially detrimental effects to another living being(s) (see Table 1 of Appendix B).
2. "Other crimes" were defined as illegal actions mainly involving the damage of property. However, "other crimes" also consisted of crimes that do not fit the "violent crimes" category (see Table 1 of Appendix B).

With the assumptions above, the following equation was formulated to rate the safeness of My City's metropolitan area:

$$R_1 = z_1 + z_2$$

where R_1 was the safety rating for 2014's crime data based on z_1 and z_2, z_1 was the z-score of My City's ratio of total crimes per 100,000 inhabitants relative to the population mean ratio of crime per 100,000 inhabitants, and z_2 was the z-score of My City's ratio of violent crimes per 100,000 inhabitants relative to the population mean ratio of violent crimes

per 100,000 inhabitants. The R_1 value also provided additional weighting to violent crimes to the overall safety rating by adding the z-score specific to violent crimes to the z-score specific to total crimes. **The higher the R-value, the more dangerous the metropolitan area.**

All values necessary for the population were calculated based on data from the FBI's table of crime data of the United States grouped by metropolitan statistical area. Metropolitan data with missing values i.e. specific property crime values, population numbers, etc. were omitted. The table of used data can be found in Table 1 of Appendix G.

Finding z_1

To calculate the z-score of My City's ratio of total crimes per 100,000 inhabitants relative to the population mean ratio, the following values were needed:

1. μ_C, the numerator of the ratio of crimes per 100,000 inhabitants for the entire population of metropolitan areas **over the course of 14 days** in 2014.
    - σ_C, the standard deviation for the total crimes per 100,000 inhabitants for the entire population of metropolitan areas **over the course of 14 days** in 2014.
2. C = the numerator of ratio of crimes per 100,000 inhabitants.

In My City's crime data, the number of crimes were recorded in a period of 14 days. Thus, the data pulled from the FBI's metropolitan area values had to be two week's worth of data also, if they were to be compared to My City's values. So find this, the average of the FBI's total crimes per 100,000 inhabitants of every metropolitan area was divided by 26, representing 26 weeks. This gave the number of crimes for two weeks out of the 52 in a year.

The μ_c was found to be 117.2929 crimes and σ_C was found to be 36.2718 crimes.

To find the z-score of My City's total crimes per 100,000 inhabitants, the total number of crimes per 100,000 inhabitants and the number of crimes per 100,000 inhabitants had to be found:

1. T_C, the total crimes in My City (11,162 crimes).
    - This value was found by summing the number of crimes in My City from 7/5/2014 to 7/18/2015.
2. P, the population of My City metropolitan area (8,800,000 people).
3. C, the numerator of the ratio of crimes per 100,000 inhabitants.

The following proportion was set up to find the number of crimes per 100,000 inhabitants:

$$\frac{C}{100{,}000} = \frac{T_C}{P}$$

C was found to equal 126.84 crimes. This value was input into the z-score equation:

$$z_1 = \frac{C - \mu_C}{\sigma_C} = 0.2632$$

Therefore, z_1 was 0.2632.

Finding z_2

To calculate the z-score of My City's ratio of violent crimes per 100,000 inhabitants, the following values were needed:

1. μ_V, the numerator of the ratio of *violent* crimes per 100,000 inhabitants for the entire population of metropolitan areas over the course of 14 days in 2014.
2. σ_V, the standard deviation for the violent crimes per 100,000 inhabitants for the entire population of metropolitan areas over the course of 14 days in 2014.
3. V, the numerator of ratio of violent crimes per 100,000 inhabitants.

μ_V was found to be 13.4854 crimes and σ_V was found to be 6.4781 crimes.

To find the z-score of My City's violent crimes per 100,000 inhabitants, the total number of violent crimes per 100,000 inhabitants and the number of crimes per 100,000 inhabitants had to be found:

1. T_V, the total of violent crimes in My City (3,919 crimes).
    - This value was found by summing the number of violent crimes in My City from 7/5/2014 to 7/18/2015.
2. P, the population of My City's metropolitan area (8,800,000 people).
3. V, the numerator of the ratio of violent crimes per 100,000 inhabitants.

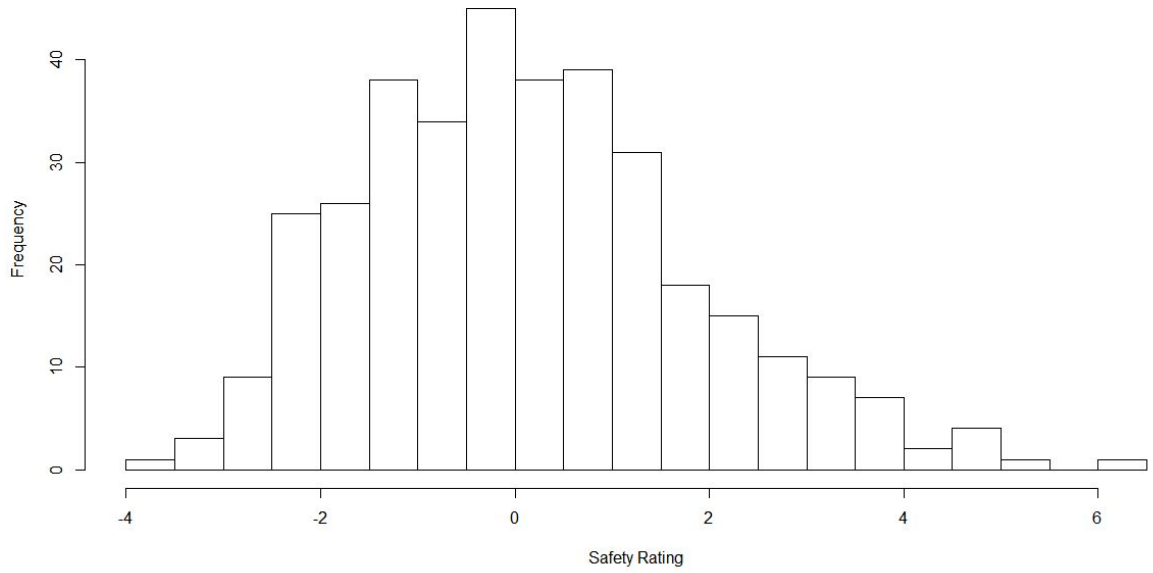
$$\frac{V}{100{,}000} = \frac{T_V}{P}$$

V was found to equal 44.534 crimes. This value was input into the z-score equation:

$$z_2 = \frac{V - \mu_V}{\sigma_V} = 4.7934$$

Therefore, z_2 was 4.7934, and the safety rating (R_1) for My City was the sum of z_1 and z_2, which equaled 5.0566.

Graph 1: Safety Rating Distribution



Since the distribution of all metropolitan areas' safety ratings (R_1) was approximately normal, the **z-score of My City's safety rating relative to the all the metropolitan areas' safety ratings could be calculated, and was found to be 2.8581**. In general, this showed that My City's metropolitan area was less safe than the average metropolitan area in the U.S.

Model 2.

The Federal Bureau of Investigation has been collected crime data using their program, the UCR program, since 1930. This system of reporting crime consists of a concept known as the Hierarchy Rule[7]. This rule categorizes crime in two categories: violent crimes and property crimes. Violent crimes consist of only murder and nonnegligent manslaughter, rape, aggravated assault, and robbery, while property crimes consist of burglary, larceny and theft, and motor vehicle theft.

Because of so, the defining of crimes in Model 1 were adjusted in Model 2 to coincide with the FBI's UCR program. Crimes of My City's crime data spreadsheet were categorized as "violent" and "property" crimes. Other crimes that did not fit the two categorizes were not used

in the rating method. Model 2's incorporation of the Hierarchy Rule in its categorization of crimes allowed for realistic comparisons to the FBI data. This would therefore yield a more realistic safety rating (R-score).

The crimes deemed "violent" and "property" crimes by the Hierarchy Rule can be found in Table 2 of Appendix C.

The formula for Model 2 was the same as that of Model 1:

$$R_2 = z_1 + z_2,$$

with **higher R_2 scores representing a more dangerous metropolitan area**.

Calculations and values for Model 2 were the same as the calculations for Model 1, with the following changes:

1. T_C, the total number of crimes in My City (6,855 crimes).
    - This value was found by summing the number of crimes in My City from 7/5/2014 to 7/18/2015 **as defined by the Hierarchy Rule**.
2. C, the numerator of the ratio of crimes per 100,000 inhabitants.
    - While calculated the same way as in Model 1, its value changed.
3. T_V, the total number of violent crimes in My City (3,249 crimes).
    - This value was calculated by summing the number of violent crimes, **as defined by the Hierarchy Rule**, in My City from 7/5/2014 to 7/18/2015.
4. V, the numerator of the ratio of violent crimes per 100,000 inhabitants.
    - While calculated the same way as in Model 1, its value changed.

$$\frac{C}{100{,}000} = \frac{T_C}{P}$$

C was found to be 77.8977 crimes.

$$\frac{V}{100{,}000} = \frac{T_V}{P}$$

V was found to be 36.9205 crimes.

The values that remained the same from Model 1 were:

1. P, the population of My City's metropolitan area
2. μ_C, the numerator of the ratio of crimes per 100,000 inhabitants for the entire population of metropolitan areas **over the course of 14 days** in 2014.
    - μ_C = 117.2929 crimes
- σ_C, the standard deviation for the total crimes per 100,000 inhabitants for the entire population of metropolitan areas **over the course of 14 days** in 2014.
    - σ_C = 36.2718 crimes
3. μ_V, the numerator of the ratio of **violent** crimes per 100,000 inhabitants for the entire population of metropolitan areas **over the course of 14 days** in 2014.
    - μ_V = 13.4854 crimes
4. σ_V, the standard deviation for the violent crimes per 100,000 inhabitants for the entire population of metropolitan areas **over the course of 14 days** in 2014.
    - σ_V = 6.4781 crimes

After using these changed and unchanged values and inputting C into z_1 and V into z_2, **z_1 and z_2 were recalculated to be -1.0861 and 3.6176, respectively.**

$$z_1 = \frac{C - \mu_C}{\sigma_C} = -1.0861$$

$$z_2 = \frac{V - \mu_V}{\sigma_V} = 3.6176$$

The new and improved safety rating (R_2) was the sum of z_1 and z_2, or 2.5315.

Since the distribution of all metropolitan areas' safety ratings (R_2) is approximately normal (as shown by Graph 1 in Model 1), the **z-score of My City's safety rating relative to the all the metropolitan areas' safety ratings could be calculated, and was found to be 1.4110**. In general, this means that My City's metropolitan area is less safe than the average metropolitan area in the U.S. Refer to Appendix G for the full distribution of safety ratings (R_2) in the U.S.

Model 3

Model 3 addresses some issues that were present in the safety ratings provided by Models 1 and 2. Models 1 and 2 calculated the safety rating by combining the Z-score of overall crime per 100,000 people with the z-score of violent crime per 100,000 people. The purpose of this was to establish an increased weight for the violent crimes, leading to a worse rating for cities with greater proportions of violent crimes. However, this method of weighting the crimes grossly overrepresented the violent crimes within Model 2's safety rating, and Model 3 served to better represent the different types of crime within the safety rating.

The primary change to Model 3 was re-adjusting the weighting scheme from the previous models. Whereas Models 1 and 2 only emphasized the violent crime category, Model 3 assigned the weight for each crime from the Hierarchy Rule individually (see Appendix C for full table).

Table 2: Sentencing Months per Crime[8]

	Mean	**Median**	
Primary Offense	**Months**	**Months**	**Number**

Murder	273	240	75
Sexual Abuse	134	120	545
Assault	31	18	775
Robbery	78	60	782
Burglary/B&E	30	21	37
Auto Theft	61	42	86
Larceny	10	2	1,408

The weights for the crimes listed under the Hierarchy Rule were quantified using their 2014 national median sentence length (in months) as reported by the U.S. Sentencing Commission.[8] Median sentence lengths were used as weight coefficients because medians are more robust to outliers than means. As a result of this weighting process, severe crimes such as murder were given a weight of 240 whereas crimes such as theft were given a weight of 2. However, high weights of severe crimes were counteracted by the high volume of less severe crimes which led to a more representative model for determining safety ratings. The safety rating range was from 0 to infinity, with lower values representing safer cities due to less crime contributing to the safety rating. Therefore, the higher the R value, the more dangerous the city and metropolitan area.

The follow equation was formulated for Model 3's rating method:

$$R_c = W_c \times C_m$$

$$R_m = \Sigma(W_c \times C_m)$$

where

W_c = weight for a crime under Hierarchy Rule

C_m = number of occurrences of such a crime per 100,000 in the metropolitan area in a fourteen day

R_c = crime rating (subset of safety rating)

R_m = safety rating for a metropolitan area

When My City's data values were inputted,

Murder = (240)(0.22727) = 54.5448

Rape = (120)(0.841) = 100.92

Robbery = (60)(4.58) = 274.8

Aggravated Assault = (18)(31.27) = 562.86

Burglary = (21)(6.432) = 135.072

Larceny/Theft = (2)(30.205) = 60.41

Motor Vehicle Test = (42)(4.341) = 182.322

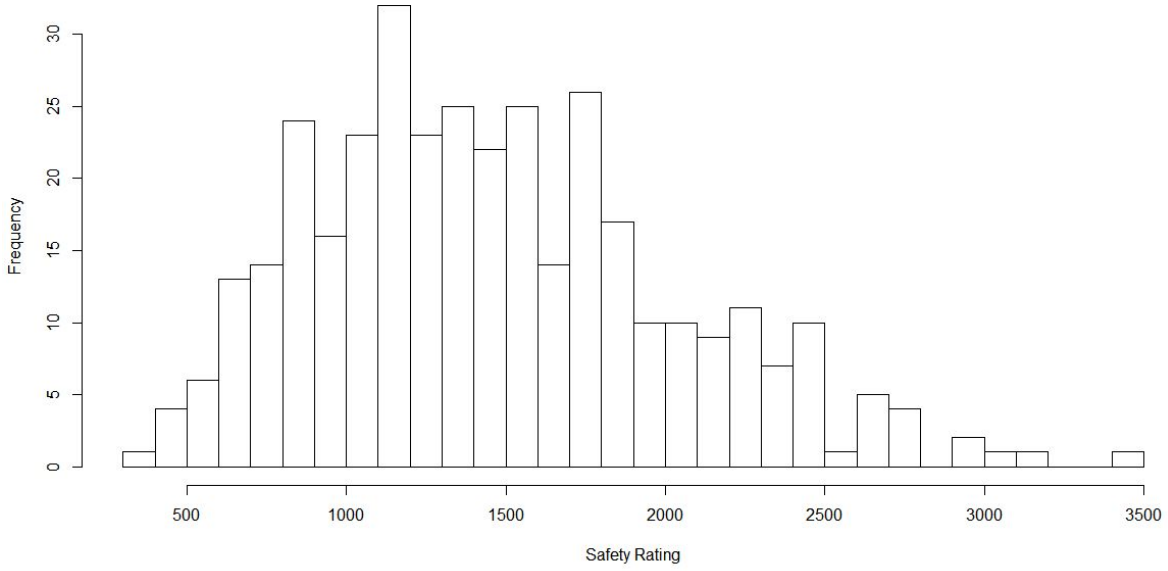
And the safety rating of My City's metropolitan area was found to be:

$$R_{My\ City} = (54.5448) + (100.92) + (274.8) + (562.86) + (135.072) + (60.41) + (182.322) = 1370.9268$$

A z-score for My City's metropolitan area was also calculated for.

$$z - score\ R_{My\ City} = \frac{1370.9268 - 1462.467}{564.8396} = -0.1620636$$

Graph 1: Weighted Number of Crimes per 100000 per Two Weeks under Hierarchy Rule



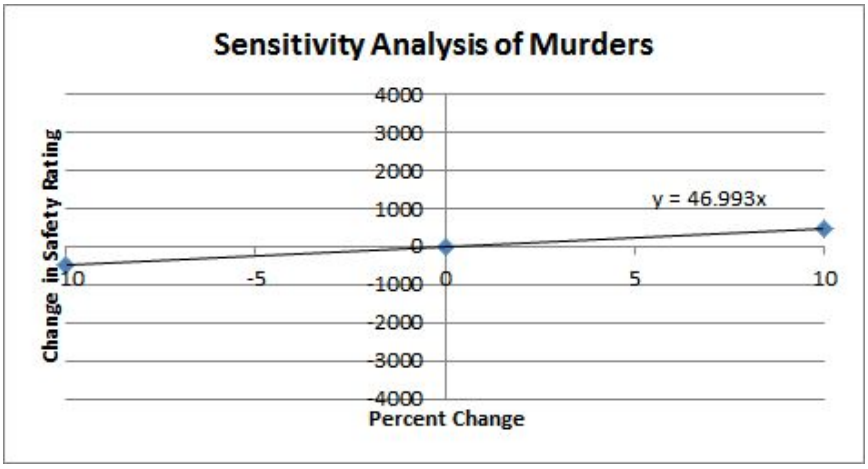
$\mu = 1462.467$

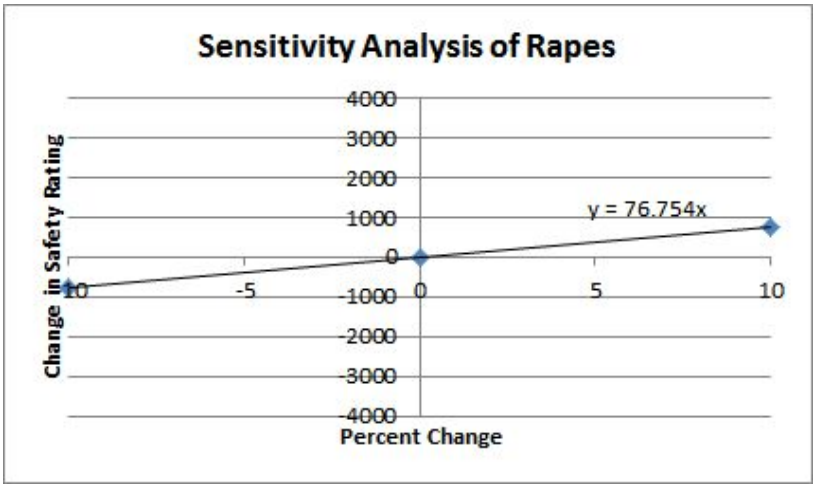
$\sigma = 564.8396$

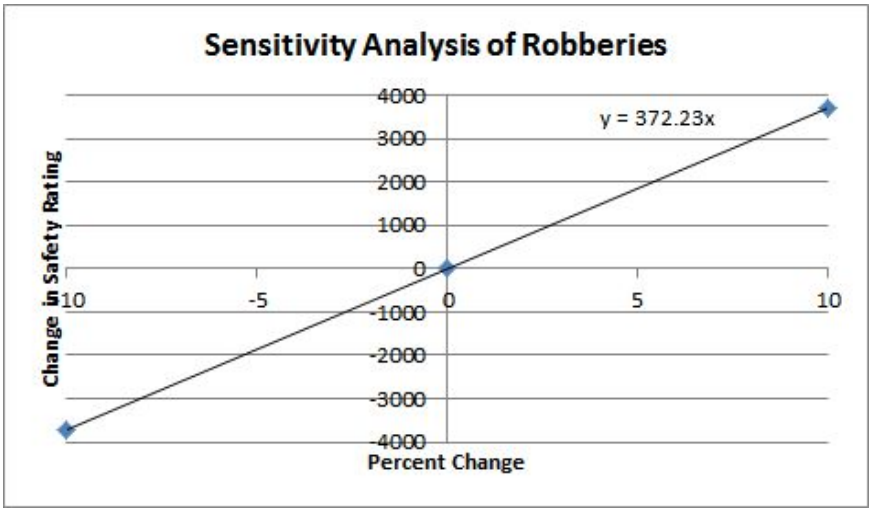
n = number of metropolitan areas = 354

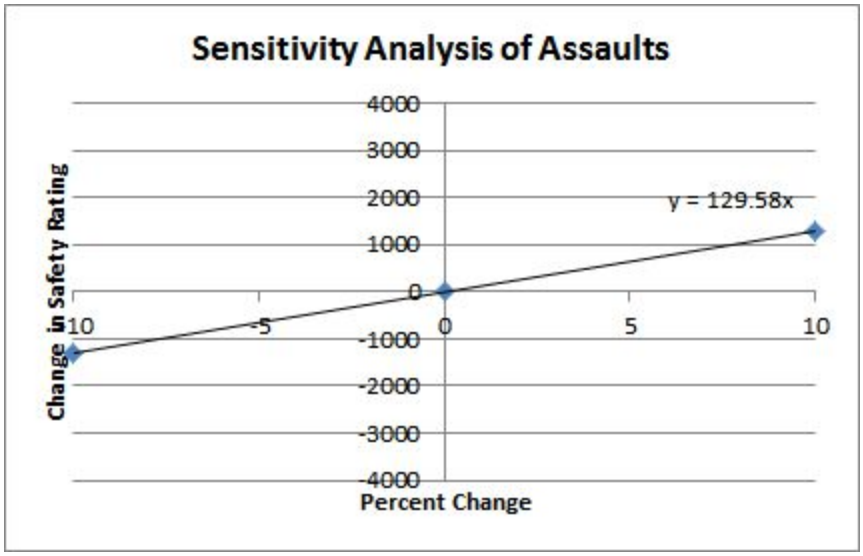
B - SENSITIVITY ANALYSIS

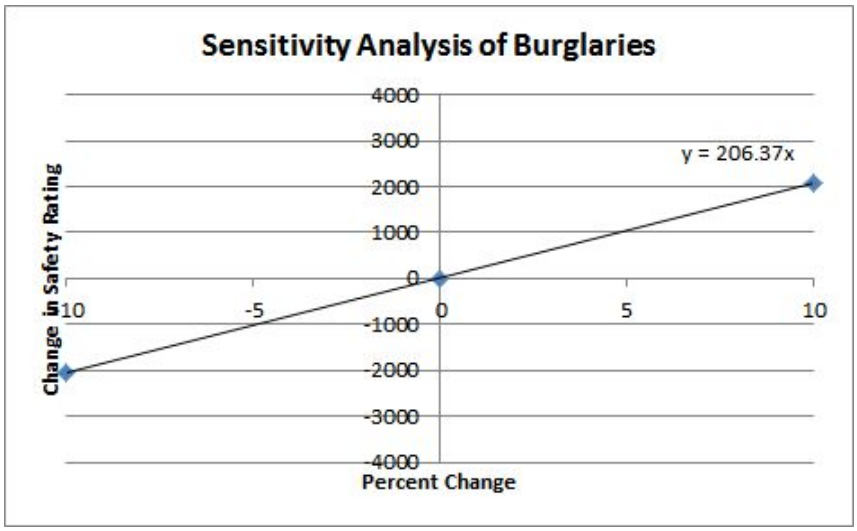
The improved weights from Model 3 helped to better represent the safety rating every year by weighing severe crimes such as murder more heavily than crimes such as larceny and theft. Because each of the crimes would have a different effect on the safety rating based upon the weighting and frequency of occurrence, sensitivity analyses[9] were conducted in order to better understand how change in crime occurrences would affect safety ratings for each year. The number of occurrences of each crime was fluctuated by 10 percent in both directions in order to observe the magnitude of change in the final result for the safety rating. The slopes in each graph represented the magnitude of the effect that each type of crime had on the safety rating relative to the other crimes.

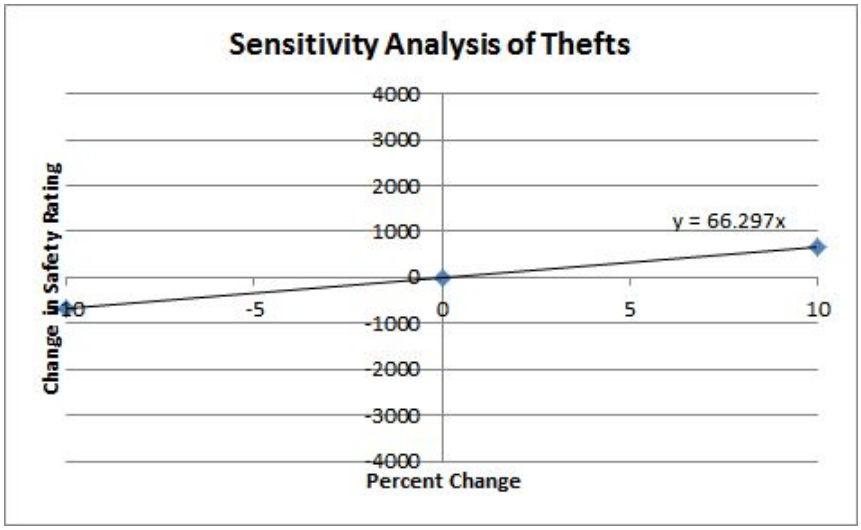

Sensitivity Analysis of Murders
Change in Safety Rating
Percent Change
y = 46.993x
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
-10
-5
0
5
10

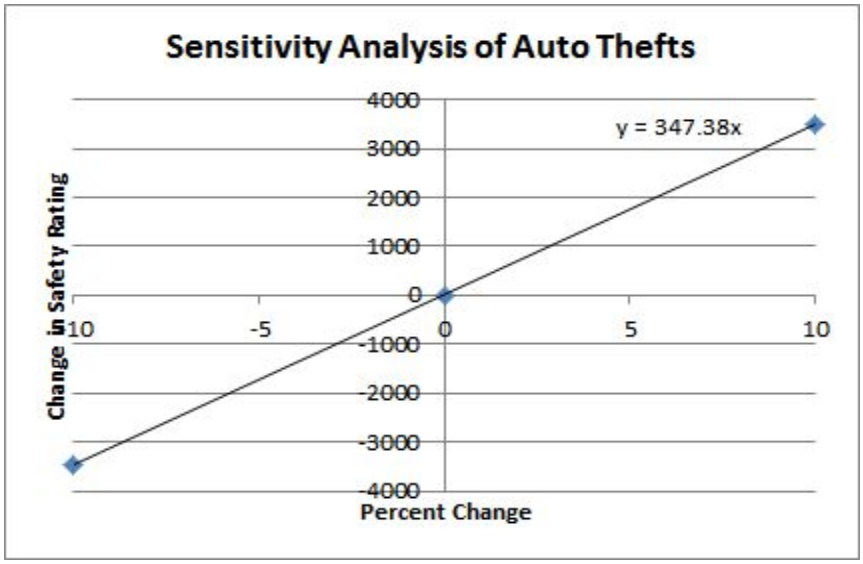

Sensitivity Analysis of Rapes
Change in Safety Rating
Percent Change
y = 76.754x
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
-10
-5
0
5
10


Sensitivity Analysis of Robberies
Change in Safety Rating
Percent Change
y = 372.23x
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
-10
-5
0
5
10


Sensitivity Analysis of Assaults
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
y = 129.58x
Change in Safety Rating
-10
-5
0
5
10
Percent Change


Sensitivity Analysis of Burglaries
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
y = 206.37x
Change in Safety Rating
-10
-5
0
5
10
Percent Change





Model 4

Since My City is described as a "large international hub of commerce, technology, finance and travel," Model 4 strives to determine if a significant relationship exists between crime in My City's crime and its economy. My City's economy was represented by its GDP, since GDP is the "godfather of the [economic] indicator world."[10] Although no economic data was provided for My City, GDP data for metropolitan areas similar to My City could be found. In order to determine which metropolitan area's GDP data could be used to represent My

City's GDP data, potential locations were determined by first choosing cities with safety ratings similar to My City's. Metropolitan areas with safety ratings within 30% of My City's safety rating were identified as potential places from which data could be used. Within this group of potential areas, only one metropolitan area, Chicago, had a population size within 10% of My City's population (the others' populations were significantly smaller than My City's). As a result, the Chicago metropolitan area's GDP[11] over the course of 10 years (from 2001 to 2011) was used to compare with its total reported crimes over the same period of time. However, since My City only had crime data for 2 weeks, the yearly GDP and total crime data for Chicago had to be divided by 26 weeks. This way, My City's government officials could predict their GDP based on their reported crimes, and, given that they already had a projected GDP value on hand, could predict their total crime based on their GDP.

A linear regression t-test was used to show the significant relationship between the GDP Index and the total crimes in Chicago over two weeks. The hypothesis that the relationship between number of crimes and GDP would be negative was tested against the null hypothesis that no relationship exists (slope would be zero). The following conditions for linear regression tests were satisfied:

1. For any fixed value of x, the response y varies according to a normal distribution. Repeated responses y are independent of each other.
2. The mean response μ_y has a straight line relationship with x:

   $$\mu_y = \alpha + \beta x$$

   The slope β and the intercept α are unknown parameters

3. The standard deviation of y (σ) is the same value for all values of x. The value of σ is unknown.

and the findings are reported below:

p-value = $1.487*10^{-6}$

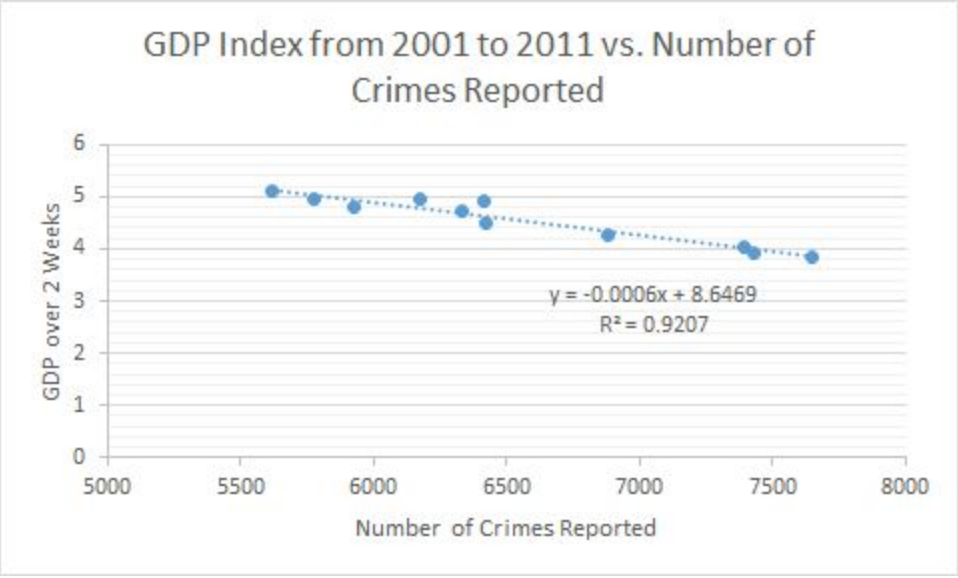
degrees of freedom = 9

$r^2 = 0.9207$

A math model with input being number of crimes over 2 weeks and output being GDP was established:

GDP over 2 weeks = 8.649 crimes -0.00006*(N)

with N representing the number of crimes in metropolitan area over 2 weeks.



If the city officials were to have a projected 2-week GDP value and sought to predict total crimes, the following model could be used:

N = -0.00003(GDP over 2 weeks - 8.2856 crimes)

Since the p-value (the probability that the slope being as negative as it was could be due to chance) at 9 degrees of freedom was so low, and since the square of the correlation coefficient was high (0.9207), it was concluded that a significant relationship exists between GDP and crime rate, and therefore the incorporation of the above models was deemed valid.

Furthermore, a model incorporating weighted values to predict number of crimes (using the scaled weighting values from Model 3) was created so that an equation that could more accurately predict GDP could be developed. This equation would be used for officials who have access to more specific data (murder, rape, robbery, assault, burglary, theft, and motor vehicle theft) and want a more accurate model. (The first equation, GDP over 2 weeks = 8.649 crimes - 0.00006*(N), only requires total crimes, whereas this equation requires specific data).

Another linear regression t-test was run for the adjusted crime values vs. GDP, and the findings are reported below:

p-value = $1.872*10^{-6}$

degrees of freedom = 9

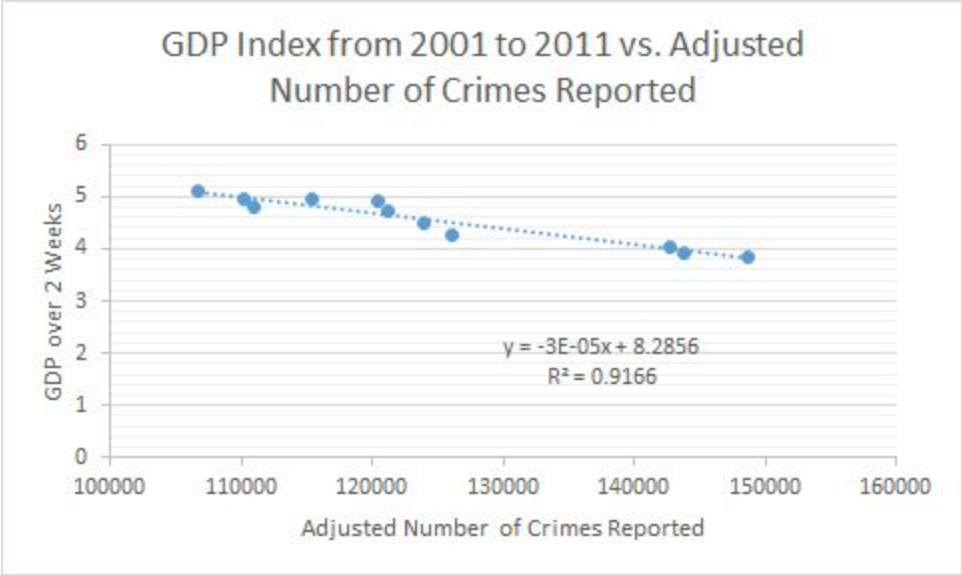
$r^2 = 0.9166$

A math model with input being number of crimes over 2 weeks and output being GDP was established:

GDP over 2 weeks = 8.2856 crimes $-0.00003*(T_C)$

$T_C = \sum(s_C * N_C)$

where T_C is total crimes, s_C is the weight or median sentence time (in months) of crime C, and N_C is the frequency of crime C over 2 weeks.



If the city officials were to have a projected 2-week GDP value and sought to predict total crimes, the following model could be used:

N = -0.00003(GDP over 2 weeks - 8.2856 crimes)

Since the p-value (the probability that the slope being as negative as it was could be due to chance) at 9 degrees of freedom was so low, and since the square of the correlation coefficient was high (0.9166), it was concluded that a significant relationship exists between GDP and crime rate, and therefore the incorporation of the above models was deemed valid.

Model 5

Assumptions

1. My City's Metropolitan Area Police Force has a limited number of police officers.
2. My City's Metropolitan Area beat system is structured like Chicago's Metropolitan Area beat system.
    - In this system, the digits of the beat represent geographic location.

- It is further explained below the rationale for using Chicago's beat system as a basis for interpreting My City's beat system.

3. The police allocated to each district are distributed evenly throughout all of the beats within the district.

The purpose of Model 5 was to determine an allocation method of the My City's Police Department's police officers to different parts of My City's Metropolitan Area. This allocation was based on the frequency of crime at each beat, as provided by original My City data. Police beats are areas broken down for patrol and statistical purposes[12]. Two metropolitan areas that prominently use beats are Houston and Chicago. Since Chicago had a more similar safety rating (R_M) and more similar population size to My City than Houston, Chicago's beat system was analyzed in order to interpret My City's beat system.

Each beat consists of three to four digits. For 3-digit beats, the first digit refers to the district, while in 4-digit beats, the first two digits refer to the district[13]. Only the district digits would be used in determining allocation because frequency of crime emanating from beats would be more volatile than frequency of crime emanating from districts.

Because of My City's limited number of police officers, they have to be stationed efficiently throughout the districts in order to have optimal response times to crimes. The patrol areas of police officers also depend on the proportion of violent crimes within each district because violent crime would more often require a rapid response by the police, and therefore require more police in the district. This process of increasing the emphasis of violent crimes is described by the equations below. The model provided the proportions of police to be stationed within each district. These values would then be multiplied by My City's number of police

officers and rounded to the nearest integer to determine exactly how many police officers to station within every district in order to optimally distribute the police force.

D_{pv} = proportion of violent crimes under Hierarchy Rule in a District D out of My City

D_{pp} = proportion of property crimes under Hierarchy Rule in a District D out of My City

D_v = number of violent crimes under Hierarchy Rule in District D

D_p = number of property crimes under Hierarchy Rule in District D

The following equations were formulated:

$$N = N_v + N_p$$

$$\Sigma(D_{prop} = 1)$$

where

N = number of crimes under Hierarchy in My City

N_v = number of violent crimes under Hierarchy Rule in My City

N_P = number of property crimes under Hierarchy Rule Crimes in My City

and,

D_{prop} = proportion of police force to send to District D.

The equation for the scaling (weighting) of violent crimes was as follows:

$$W_v = \Sigma(\frac{C_w \times C_v}{N_v})$$

where

W_v = weight for violent crimes in My City

C_w = weight factor associated with Hierarchy Rule Crime C

C_v = Number of Occurrences of a Violent Hierarchy Rule Crime.

And the equation for the scaling of property crimes was as follows:

$$W_p = \Sigma(\frac{C_w \times C_p}{N_p})$$

where

W_p = weight for property crimes in My City

C_w = weight factor associated with Hierarchy Rule Crime C

C_p = number of occurrences of a property crimes under Hierarchy Rule

The proportions of crimes under the Hierarchy Rule Crimes are displayed in the equations below:

$$D_{pv} = \frac{D_v}{N_v}$$

$$D_{pp} = \frac{D_p}{N_p}$$

The equation for the proportion of district police distributed to beats is below:

$$D_{prop} = \frac{(W_v \times D_{pv}) + (W_p \times D_{pp})}{W_v + W_p}$$

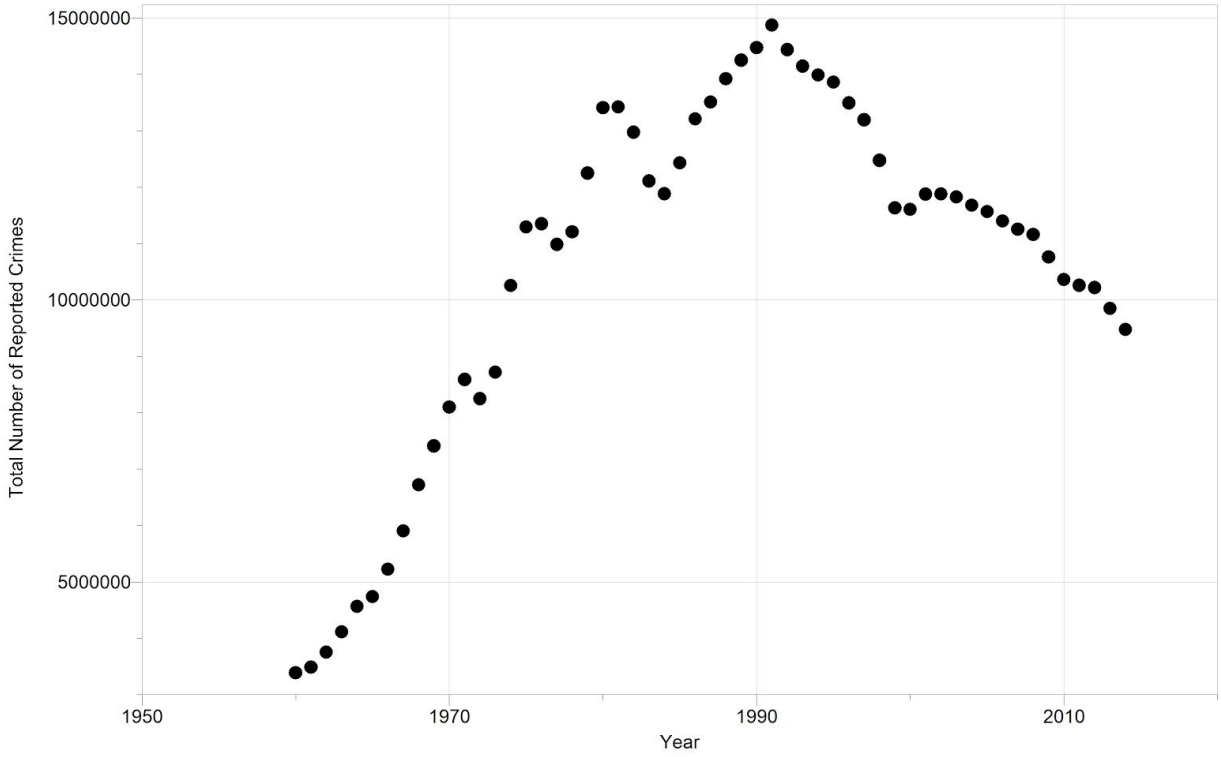
The districts' proportional allocation of police officers can be found in Table 1 of Appendix E.

References

1. "The DC Sniper Beltway Attacks." *Crime Library:*. National Museum of Crime & Punishment, 2015. Web. 12 Nov. 2015.
2. "Crime Index for Country 2015 Mid Year." *Crime Index by Country 2015 Mid Year*. Numbeo, 2009. Web. 12 Nov. 2015.
3. "Countries Compared by Crime Total Crimes. International Statistics at NationMaster.com." *NationMaster.com*. NationMaster, 2003. Web. 12 Nov. 2015.
4. "Persons Arrested." *FBI*. FBI, 16 May 2013. Web. 12 Nov. 2015.
5. "Crime in U.S." *FBI*. FBI, 19 May 2014. Web. 12 Nov. 2015.
6. "Uniform Crime Reports." *FBI*. FBI, 09 May 2012. Web. 11 Nov. 2015.
7. "Violent Crime." *FBI*. FBI, 25 July 2011. Web. 12 Nov. 2015.
8. "USSC Interactive Sourcebook - Table of Contents." *USSC Interactive Sourcebook - Table of Contents*. U.S. Sentencing Commission, 2000. Web. 12 Nov. 2015.
9. "Conducting Sensitivity Analysis." *Conducting Sensitivity Analysis*. University of Arizona, 2014. Web. 11 Nov. 2015.
10. "Economic Indicators: Gross Domestic Product (GDP) | Investopedia."*Investopedia*. N.p., 03 Dec. 2003. Web. 12 Nov. 2015.
11. "Regional Data." *U.S. Bureau of Economic Analysis (BEA)*. N.p., 2000. Web. 12 Nov. 2015.
12. "Neighborhood (Police Beat) Crime Statistics." *Neighborhood (Police Beat) Crime Statistics*. N.p., n.d. Web. 12 Nov. 2015.
13. "KnowYourDistrict." *KnowYourDistrict*. N.p., n.d. Web. 12 Nov. 2015.

Appendix A

Graph 1: Total Number of Reported Crimes from 1960 - 2014



Appendix B

Table 1: My City's Categorized Crime Data

Key P = Decided by Primary Description of Crime S = Decided by Secondary Description of Crime	
Violent Crimes (3919 total crimes)	**Other Crimes (7243 total crimes)**
Assault (P) Battery (P) Criminal Sexual Assault (P) Homicide (P) Interference w/ Public Officer (P) Intimidation (P) Kidnapping (P) Offense Involving Children (P) Animal Abuse/Neglect (S) Harassment (S) Obscene Phone Calls (S) Other Crimes Against Person (S) Sex Offender (S) Telephone Threat (S) Violate Order of Protection (S) Violent Offender (S) Bomb Threat (S) Mob Action (S) Peeping Tom (S) Reckless Conduct (S) Robbery (P) Sex Offense (P) Stalking (P)	Arson (P) Burglary (P) Concealed Carry License Violation (P) Criminal Damage (P) Criminal Trespass (P) Deceptive Practice (P) Gambling (P) Liquor Law Violation (P) Motor Vehicle Theft (P) Narcotics (P) Other Narcotic Violation (P) False/Stolen/Altered Temporary Registration Permits (S) Gun Offender (S) Hazardous Materials Violation (S) License Violation (S) Other Vehicle Offense (S) Other Weapons Violation (S) Parole Violation (S) Possession of Burglary Tools (S) Probation Violation (S) Vehicle Title/Registration Offender Arson Threat (S) False Police Report (S) Other Violation (S) Public Demonstration (S) Theft (P) Weapons Violation (P)

Appendix C

Table 1: My City's Categorized Crime Data under Hierarchy Rule

Key P = Decided by Primary Description of Crime S = Decided by Secondary Description of Crime	
Violent Crimes (3249 total crimes)	**Property Crimes (3630 total crimes)**
Assault (P) Battery (P) Criminal Sexual Assault (P) Homicide (P) Sex Offender (S) Robbery (P) Sex Offense (P) Stalking (P)	Arson (P) Burglary (P) Motor Vehicle Theft (P) Theft (P)

Table 3: Sentencing Months per Crime (full)

	Mean	**Median**	
Primary Offense	**Months**	**Months**	**Number**
Total	**44**	**24**	**75836**
Murder	273	240	75
Manslaughter	54	37	49
Kidnapping/Hostage Taking	201	168	50
Sexual Abuse	134	120	545
Assault	31	18	775
Robbery	78	60	782
Arson	62	49	54
Drugs - Trafficking	68	51	21323
Drugs - Communication Facility	31	24	344
Drugs - Simple Possession	5	6	2344

Firearms	82	57	7925
Burglary/B&E	30	21	37
Auto Theft	61	42	86
Larceny	10	2	1408
Fraud	27	14	7614
Embezzlement	10	6	334
Forgery/Counterfeiting	18	12	713
Bribery	21	12	241
Tax	13	9	649
Money Laundering	32	18	886
Racketeering/Extortion	88	58	864
Gambling/Lottery	5	3	117
Civil Rights	36	18	58
Immigration	15	10	22238
Child Pornography	137	97	1925
Prison Offenses	15	12	448
Administration of Justice Offenses	18	12	1242
Environmental/Wildlife	4	0	202
National Defense	45	35	108
Antitrust	22	16	19
Food & Drug	8	0	114
Other Miscellaneous Offenses	18	0	2267

Appendix D

Table 1: GDP Index from 2001 to 2011 vs. Number of Crimes Reported

Year	Number of Crimes Reported	GDP Index
2001	7647.153846	100
2002	7429.307692	102
2003	7396.269231	105.1
2004	6883.5	110.8
2005	6422.423077	116.6
2006	6336.846154	123.2
2007	6175.615385	128.5
2008	6413.692308	127.6
2009	5930.769231	125.1
2010	5776.423077	128.4
2011	5620.923077	132.5

Graph 1: GDP Index from 2001 to 2011 vs. Number of Crimes Reported

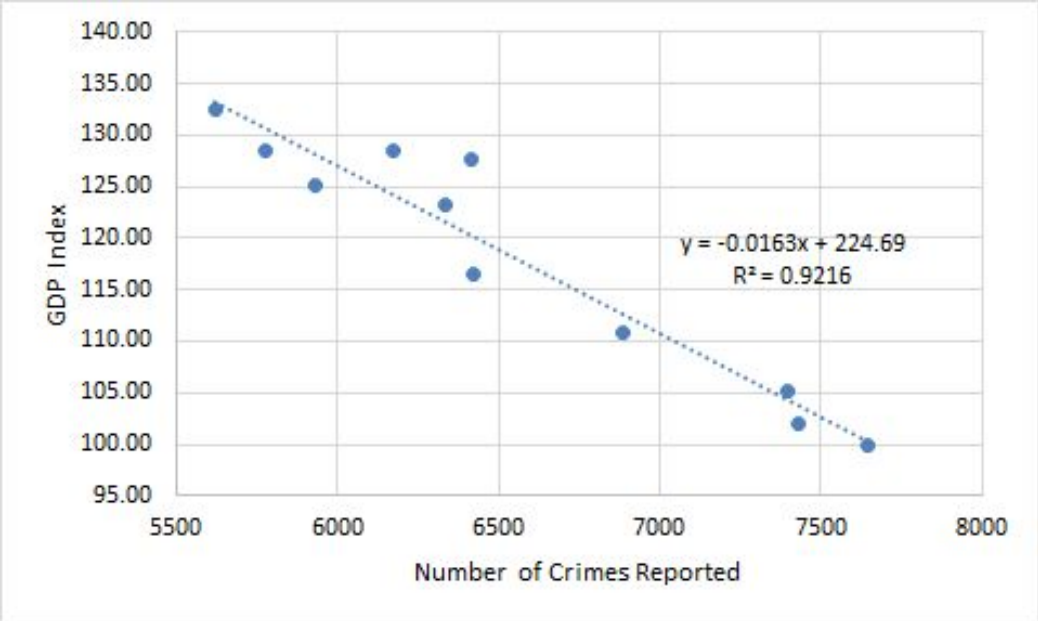
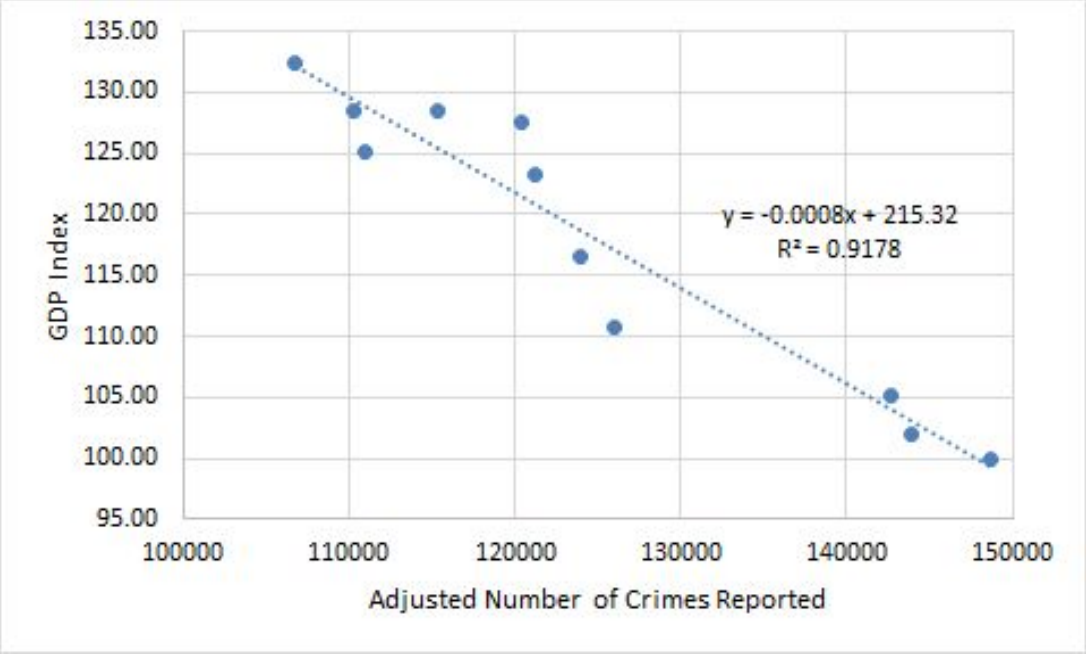


Table 2: GDP Index from 2001 to 2011 vs. Adjusted Number of Crimes Reported

Year	Adjusted Number of Crimes Reported	GDP Index
2001	148730.5385	100
2002	143838.3846	102
2003	142691.6923	105.1
2004	126030.7692	110.8
2005	124000.8462	116.6
2006	121181.7308	123.2
2007	115361.5769	128.5
2008	120441.8846	127.6
2009	110904.7692	125.1
2010	110234.5	128.4
2011	106745.8462	132.5

Graph 2: GDP Index from 2001 to 2011 vs. Adjusted Number of Crimes Reported



Appendix E

Table 1: Correlation Between the Districts of Beats and the Proportion of Officers Assigned to District to Handle Crime

District Number	Total Violent Cases	Total Non-Violent Cases	Officer Proportion per District
1	80	238	0.03464464258
2	121	159	0.03868759105
3	213	153	0.05944512901
4	228	203	0.06630773324
5	183	137	0.0514512015
6	232	234	0.06934314949
7	253	160	0.06912574235
8	158	248	0.05327280079
9	182	171	0.05354093053
10	195	143	0.05462148069
11	244	135	0.06534932748
12	140	208	0.04640226641
14	92	163	0.03228832941
15	150	85	0.04031078522
16	66	143	0.02494178442
17	76	121	0.02574148629
18	77	261	0.0355236964
19	121	292	0.04776211924
20	44	149	0.02028950801
22	108	65	0.02928303759
24	93	98	0.02808348479
25	181	175	0.05358377351

Appendix F

Table 1: Metropolitan Areas and their Assigned Numbers

Number	Metropolitan Area
1	Includes Callahan, Jones, and Taylor Counties
2	Includes Baker, Dougherty, Lee, Terrell, and Worth Counties3
3	Includes Linn County
4	Includes Albany, Rensselaer, Saratoga, Schenectady, and Schoharie Counties
5	Includes Bernalillo, Sandoval, Torrance, and Valencia Counties
6	Includes Grant and Rapides Parishes
7	Includes Warren County, NJ and Carbon, Lehigh, and Northampton Counties, PA
8	Includes Blair County
9	Includes Armstrong, Carson, Oldham, Potter, and Randall Counties
10	Includes Story County
11	Includes Anchorage Municipality and Matanuska-Susitna Borough
12	Includes Washtenaw County
13	Includes Calhoun County
14	Includes Calumet and Outagamie Counties
15	Includes Buncombe, Haywood, Henderson, and Madison Counties
16	Includes Clarke, Madison, Oconee, and Oglethorpe Counties3
17	Includes Barrow, Bartow, Butts, Carroll, Cherokee, Clayton, Cobb, Coweta, Dawson, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Haralson, Heard, Henry, Jasper, Lamar, Meriwether, Morgan, Newton, Paulding, Pickens, Pike, Rockdale, Spalding, and Walton Counties3
18	Includes Atlantic County
19	Includes Lee County
20	Includes Burke, Columbia, Lincoln, McDuffie, and Richmond Counties, GA3 and Aiken and Edgefield Counties, SC
21	Includes Bastrop, Caldwell, Hays, Travis, and Williamson Counties
22	Includes Kern County
23	Includes Anne Arundel, Baltimore, Carroll, Harford, Howard, and Queen Anne's Counties and Baltimore City
24	Includes Penobscot County
25	Includes Barnstable County
26	Includes Calhoun County
27	Includes Bay County
28	Includes Hardin, Jefferson, Newton, and Orange Counties
29	Includes Fayette and Raleigh Counties

30	Includes Whatcom County
31	Includes Deschutes County
32	Includes Carbon, Golden Valley, and Yellowstone Counties
33	Includes Broome and Tioga Counties
34	Includes Burleigh, Morton, Oliver, and Sioux Counties
35	Includes Floyd, Giles, Montgomery, and Pulaski Counties and Radford City
36	Includes DeWitt and McLean Counties
37	Includes Monroe and Owen Counties
38	Includes Ada, Boise, Canyon, Gem, and Owyhee Counties
39	Includes Allen, Butler, Edmonson, and Warren Counties
40	Includes Kitsap County
41	Includes Fairfield County
42	Includes Cameron County
43	Includes Brantley, Glynn, and McIntosh Counties3
44	Includes Alamance County
45	Includes St. Mary's County
46	Includes Carroll and Stark Counties
47	Includes Lee County
48	Includes Alexander County, IL and Bollinger and Cape Girardeau Counties, MO
49	Includes Carson City
50	Includes Natrona County
51	Includes Benton, Jones, and Linn Counties
52	Includes Franklin County
53	Includes Champaign, Ford, and Piatt Counties
54	Includes Boone, Clay, and Kanawha Counties
55	Includes Berkeley, Charleston, and Dorchester Counties
56	Includes Cabarrus, Gaston, Iredell, Lincoln, Mecklenburg, Rowan, and Union Counties, NC and Chester, Lancaster, and York Counties, SC
57	Includes Albemarle, Buckingham, Fluvanna, Greene, and Nelson Counties and Charlottesville City
58	Includes Catoosa, Dade, and Walker Counties, GA3 and Hamilton, Marion, and Sequatchie Counties, TN
59	Includes Laramie County
60	Includes the Metropolitan Divisions of Chicago-Naperville-Arlington Heights, IL; Elgin, IL; Gary, IN; and Lake County-Kenosha County, IL-WI
61	Includes Cook, DuPage, Grundy, Kendall, McHenry, and Will Counties
62	Includes DeKalb and Kane Counties

63	Includes Jasper, Lake, Newton, and Porter Counties
64	Includes Lake County, IL and Kenosha County, WI
65	Includes Butte County
66	Includes Dearborn, Ohio, and Union Counties, IN; Boone, Bracken, Campbell, Gallatin, Grant, Kenton, and Pendleton Counties, KY; and Brown, Butler, Clermont, Hamilton, and Warren Counties, OH
67	Includes Christian and Trigg Counties, KY and Montgomery County, TN
68	Includes Bradley and Polk Counties
69	Includes Kootenai County
70	Includes Brazos, Burleson, and Robertson Counties
71	Includes El Paso and Teller Counties
72	Includes Boone County
73	Includes Calhoun, Fairfield, Kershaw, Lexington, Richland, and Saluda Counties
74	Includes Russell County, AL and Chattahoochee, Harris, Marion, and Muscogee Counties, GA3
75	Includes Bartholomew County
76	Includes Delaware, Fairfield, Franklin, Hocking, Licking, Madison, Morrow, Perry, Pickaway, and Union Counties
77	Includes Aransas, Nueces, and San Patricio Counties
78	Includes Benton County
79	Includes Okaloosa and Walton Counties
80	Includes Allegany County, MD and Mineral County, WV
81	Includes Murray and Whitfield Counties
82	Includes Baldwin County
83	Includes Henry, Mercer, and Rock Island Counties, IL and Scott County, IA
84	Includes Lawrence and Morgan Counties
85	Includes Macon County
86	Includes Flagler and Volusia Counties
87	Includes Dallas, Guthrie, Madison, Polk, and Warren Counties
88	Includes the Metropolitan Divisions of Detroit-Dearborn-Livonia and Warren-Troy-Farmington Hills
89	Includes Wayne County
90	Includes Lapeer, Livingston, Macomb, Oakland, and St. Clair Counties
91	Includes Kent County
92	Includes Dubuque County
93	Includes Carlton and St. Louis Counties, MN and Douglas County, WI
94	Includes Chatham, Durham, Orange and Person Counties
95	Includes Monroe County
96	Includes Chippewa and Eau Claire Counties

97	Includes Imperial County
98	Includes Hardin, Larue, and Meade Counties
99	Includes Elkhart County
100	Includes Chemung County
101	Includes El Paso and Hudspeth Counties
102	Includes Posey, Vanderburgh, and Warrick Counties, IN and Henderson County, KY
103	Includes Fairbanks North Star Borough
104	Includes Clay County, MN and Cass County, ND
105	Includes San Juan County
106	Includes Cumberland and Hoke Counties
107	Includes Coconino County
108	Includes Genesee County
109	Includes Darlington and Florence Counties
110	Includes Colbert and Lauderdale Counties
111	Includes Fond du Lac County
112	Includes Larimer County
113	Includes Crawford and Sebastian Counties, AR and Le Flore and Sequoyah Counties, OK
114	Includes Allen, Wells, and Whitley Counties
115	Includes Fresno County
116	Includes Alachua and Gilchrist Counties
117	Includes Hall County3
118	Includes Adams County
119	Includes Warren and Washington Counties
120	Includes Wayne County
121	Includes Polk County, MN and Grand Forks County, ND
122	Includes Hall, Hamilton, Howard, and Merrick Counties
123	Includes Mesa County
124	Includes Cascade County
125	Includes Weld County
126	Includes Guilford, Randolph, and Rockingham Counties
127	Includes Pitt County
128	Includes Tangipahoa Parish
129	Includes Kings County
130	Includes Cumberland, Dauphin, and Perry Counties
131	Includes Rockingham County and Harrisonburg City

132	Includes Hartford, Middlesex, and Tolland Counties
133	Includes Alexander, Burke, Caldwell, and Catawba Counties
134	Includes Beaufort and Jasper Counties
135	Includes Liberty and Long Counties3
136	Includes Citrus County
137	Includes Lafourche and Terrebonne Parishes
138	Includes Austin, Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller Counties
139	Includes Limestone and Madison Counties
140	Includes Bonneville, Butte, and Jefferson Counties
141	Includes Boone, Brown, Hamilton, Hancock, Hendricks, Johnson, Madison, Marion, Morgan, Putnam, and Shelby Counties
142	Includes Johnson and Washington Counties
143	Includes Jackson County
144	Includes Copiah, Hinds, Madison, Rankin, Simpson, and Yazoo Counties
145	Includes Chester, Crockett, and Madison Counties
146	Includes Baker, Clay, Duval, Nassau, and St. Johns Counties
147	Includes Rock County
148	Includes Callaway, Cole, Moniteau, and Osage Counties
149	Includes Carter, Unicoi, and Washington Counties
150	Includes Cambria County
151	Includes Craighead and Poinsett Counties
152	Includes Jasper and Newton Counties
153	Includes Kalawao and Maui Counties
154	Includes Kalamazoo and Van Buren Counties
155	Includes Kankakee County
156	Includes Johnson, Leavenworth, Linn, Miami, and Wyandotte Counties, KS and Bates, Caldwell, Cass, Clay, Clinton, Jackson, Lafayette, Platte, and Ray Counties, MO
157	Includes Benton and Franklin Counties
158	Includes Bell, Coryell, and Lampasas Counties
159	Includes Hawkins and Sullivan Counties, TN and Scott and Washington Counties and Bristol City, VA
160	Includes Ulster County
161	Includes Anderson, Blount, Campbell, Grainger, Knox, Loudon, Morgan, Roane, and Union Counties
162	Includes Howard County
163	Includes Houston County, MN and La Crosse County, WI
164	Includes Benton, Carroll, and Tippecanoe Counties
165	Includes Mohave County

166	Includes Polk County
167	Includes Lancaster County
168	Includes Clinton, Eaton, and Ingham Counties
169	Includes Webb County
170	Includes Dona Ana County
171	Includes Clark County
172	Includes Comanche and Cotton Counties
173	Includes Lebanon County
174	Includes Nez Perce County, ID and Asotin County, WA
175	Includes Androscoggin County
176	Includes Allen County
177	Includes Lancaster and Seward Counties
178	Includes Faulkner, Grant, Lonoke, Perry, Pulaski, and Saline Counties
179	Includes Gregg, Rusk, and Upshur Counties
180	Includes Cowlitz County
181	Includes the Metropolitan Divisions of Anaheim-Santa Ana-Irvine and Los Angeles-Long Beach-Glendale
182	Includes Orange County
183	Includes Los Angeles County
184	Includes Clark, Floyd, Harrison, Scott, and Washington Counties, IN and Bullitt, Henry, Jefferson, Oldham, Shelby, Spencer, and Trimble Counties, KY
185	Includes Crosby, Lubbock, and Lynn Counties
186	Includes Amherst, Appomattox, Bedford, and Campbell Counties and Bedford and Lynchburg Cities
187	Includes Madera County
188	Includes Columbia, Dane, Green, and Iowa Counties
189	Includes Hillsborough County
190	Includes Pottawatomie and Riley Counties
191	Includes Blue Earth and Nicollet Counties
192	Includes Richland County
193	Includes Hidalgo County
194	Includes Jackson County
195	Includes Crittenden County, AR; Benton, DeSoto, Marshall, Tate, and Tunica Counties, MS; and Fayette, Shelby, and Tipton Counties, TN
196	Includes Merced County
197	Includes the Metropolitan Divisions of Fort Lauderdale-Pompano Beach-Deerfield Beach, Miami-Miami Beach-Kendall, and West Palm Beach-Boca Raton-Delray Beach

198	Includes Broward County
199	Includes Miami-Dade County
200	Includes Palm Beach County
201	Includes La Porte County
202	Includes Midland County
203	Includes Martin and Midland Counties
204	Includes Milwaukee, Ozaukee, Washington, and Waukesha Counties
205	Includes Anoka, Carver, Chisago, Dakota, Hennepin, Isanti, Le Sueur, Mille Lacs, Ramsey, Scott, Sherburne, Sibley, Washington, and Wright Counties, MN and Pierce and St. Croix Counties, WI
206	Includes Missoula County
207	Includes Mobile County
208	Includes Stanislaus County
209	Includes Autauga, Elmore, Lowndes, and Montgomery Counties
210	Includes Monongalia and Preston Counties
211	Includes Hamblen and Jefferson Counties
212	Includes Skagit County
213	Includes Delaware County
214	Includes Muskegon County
215	Includes Napa County
216	Includes Collier County
217	Includes Cannon, Cheatham, Davidson, Dickson, Hickman, Macon, Maury, Robertson, Rutherford, Smith, Sumner, Trousdale, Williamson, and Wilson Counties
218	Includes Craven, Jones, and Pamlico Counties
219	Includes New Haven County
220	Includes Dutchess and Putnam Counties
221	Includes Nassau and Suffolk Counties
222	Includes Essex, Hunterdon, Morris, Somerset, Sussex, and Union Counties, NJ and Pike County, PA
223	Includes Berrien County
224	Includes Manatee and Sarasota Counties
225	Includes New London County
226	Includes Marion County
227	Includes Cape May County
228	Includes Box Elder, Davis, Morgan, and Weber Counties
229	Includes Canadian, Cleveland, Grady, Lincoln, Logan, McClain, and Oklahoma Counties
230	Includes Thurston County

231	Includes Harrison, Mills, and Pottawattamie Counties, IA and Cass, Douglas, Sarpy, Saunders, and Washington Counties, NE
232	Includes Lake, Orange, Osceola, and Seminole Counties
233	Includes Winnebago County
234	Includes Daviess, Hancock, and McLean Counties
235	Includes Ventura County
236	Includes Brevard County
237	Includes Bay and Gulf Counties
238	Includes Escambia and Santa Rosa Counties
239	Includes Marshall, Peoria, Stark, Tazewell, and Woodford Counties
240	Includes the Metropolitan Divisions of Camden, NJ; Montgomery County-Bucks County-Chester County, PA; Philadelphia, PA; and Wilmington, DE-MD-NJ
241	Includes Burlington, Camden, and Gloucester Counties
242	Includes Bucks, Chester, and Montgomery Counties
243	Includes Delaware and Philadelphia Counties
244	Includes New Castle County, DE; Cecil County, MD; and Salem County, NJ
245	Includes Cleveland, Jefferson, and Lincoln Counties
246	Includes Allegheny, Armstrong, Beaver, Butler, Fayette, Washington, and Westmoreland Counties
247	Includes Berkshire County
248	Includes Cumberland, Sagadahoc, and York Counties
249	Includes Clackamas, Columbia, Multnomah, Washington, and Yamhill Counties, OR and Clark and Skamania Counties, WA
250	Includes Martin and St. Lucie Counties
251	Includes Bristol County, MA and Bristol, Kent, Newport, Providence, and Washington Counties RI
252	Includes Pueblo County
253	Includes Charlotte County
254	Includes Racine County
255	Includes Custer, Meade, and Pennington Counties
256	Includes Berks County
257	Includes Shasta County
258	Includes Storey and Washoe Counties
259	Includes Amelia, Caroline, Charles City, Chesterfield, Dinwiddie, Goochland, Hanover, Henrico, King William, New Kent, Powhatan, Prince George, and Sussex Counties and Colonial Heights, Hopewell, Petersburg, and Richmond Cities
260	Includes Riverside and San Bernardino Counties
261	Includes Botetourt, Craig, Franklin, and Roanoke Counties and Roanoke and Salem Cities
262	Includes Dodge, Fillmore, Olmsted, and Wabasha Counties
263	Includes Livingston, Monroe, Ontario, Orleans, Wayne, and Yates Counties

264	Includes Boone and Winnebago Counties
265	Includes Edgecombe and Nash Counties
266	Includes El Dorado, Placer, Sacramento, and Yolo Counties
267	Includes Saginaw County
268	Includes Marion and Polk Counties
269	Includes Monterey County
270	Includes Sussex County, DE and Somerset, Wicomico, and Worcester Counties, MD
271	Includes Salt Lake and Tooele Counties
272	Includes Irion and Tom Green Counties
273	Includes Atascosa, Bandera, Bexar, Comal, Guadalupe, Kendall, Medina, and Wilson Counties
274	Includes San Diego County
275	Includes the Metropolitan Divisions of Oakland-Hayward-Berkeley, San Francisco-Redwood City-South San Francisco, and San Rafael
276	Includes Alameda and Contra Costa Counties
277	Includes San Francisco and San Mateo Counties
278	Includes Marin County
279	Includes San Benito and Santa Clara Counties
280	Includes San Luis Obispo County
281	Includes Santa Cruz County
282	Includes Santa Fe County
283	Includes Santa Barbara County
284	Includes Sonoma County
285	Includes Bryan, Chatham, and Effingham Counties3
286	Includes Lackawanna, Luzerne, and Wyoming Counties
287	Includes the Metropolitan Divisions of Seattle-Bellevue-Everett and Tacoma-Lakewood
288	Includes King and Snohomish Counties
289	Includes Pierce County
290	Includes Indian River County
291	Includes Highlands County
292	Includes Sheboygan County
293	Includes Grayson County
294	Includes Plymouth and Woodbury Counties, IA; Dakota and Dixon Counties, NE; and Union County, SD
295	Includes Lincoln, McCook, Minnehaha, and Turner Counties
296	Includes St. Joseph County, IN and Cass County, MI
297	Includes Spartanburg and Union Counties
298	Includes Pend Oreille, Spokane, and Stevens Counties

299	Includes Menard and Sangamon Counties
300	Includes Hampden and Hampshire Counties
301	Includes Christian, Dallas, Greene, Polk, and Webster Counties
302	Includes Clark County
303	Includes Centre County
304	Includes Augusta County and Staunton and Waynesboro Cities
305	Includes Benton and Stearns Counties
306	Includes Washington County
307	Includes Doniphan County, KS and Andrew, Buchanan, and DeKalb Counties, MO
308	Includes Bond, Calhoun, Clinton, Jersey, Macoupin, Madison, Monroe, and St. Clair Counties, IL and Franklin, Jefferson, Lincoln, St. Charles, St. Louis, and Warren Counties and St. Louis City, MO
309	Includes San Joaquin County
310	Includes Sumter County
311	Includes Madison, Onondaga, and Oswego Counties
312	Includes Gadsden, Jefferson, Leon, and Wakulla Counties
313	Includes Hernando, Hillsborough, Pasco, and Pinellas Counties
314	Includes Little River and Miller Counties, AR and Bowie County, TX
315	Includes Sumter County
316	Includes Jackson, Jefferson, Osage, Shawnee, and Wabaunsee Counties
317	Includes Mercer County
318	Includes Creek, Okmulgee, Osage, Pawnee, Rogers, Tulsa, and Wagoner Counties
319	Includes Hale, Pickens, and Tuscaloosa Counties
320	Includes Herkimer and Oneida Counties
321	Includes Brooks, Echols, Lanier, and Lowndes Counties3
322	Includes Solano County
323	Includes Goliad and Victoria Counties
324	Includes Cumberland County
325	Includes Currituck and Gates Counties, NC and Gloucester, Isle of Wight, James City, Mathews, and York Counties and Chesapeake, Hampton, Newport News, Norfolk, Poquoson, Portsmouth, Suffolk, Virginia Beach, and Williamsburg Cities, VA
326	Includes Tulare County
327	Includes Falls and McLennan Counties
328	Includes Columbia and Walla Walla Counties
329	Includes Houston, Peach, and Pulaski Counties3
330	Includes the Metropolitan Divisions of Silver Spring-Frederick-Rockville, MD and Washington-Arlington-Alexandria, DC-VA-MD-WV

331	Includes Frederick and Montgomery Counties
332	Includes District of Columbia; Calvert, Charles, and Prince George's Counties, MD; Arlington, Clarke, Culpeper, Fairfax, Fauquier, Loudoun, Prince William, Rappahannock, Spotsylvania, Stafford, and Warren Counties and Alexandria, Fairfax, Falls Church, Fredericksburg, Manassas, and Manassas Park Cities, VA; and Jefferson County, WV
333	Includes Black Hawk, Bremer, and Grundy Counties
334	Includes Jefferson County
335	Includes Marathon County
336	Includes Chelan and Douglas Counties
337	Includes Belmont County, OH and Marshall and Ohio Counties, WV
338	Includes Archer, Clay, and Wichita Counties
339	Includes Lycoming County
340	Includes New Hanover and Pender Counties
341	Includes Frederick County and Winchester City, VA and Hampshire County, WV
342	Includes Davidson, Davie, Forsyth, Stokes, and Yadkin Counties
343	Includes Windham County, CT and Worcester County, MA
344	Includes Yakima County
345	Includes York County
346	Includes Sutter and Yuba Counties
347	Includes Yuma County
348	Includes Aguada, Aguadilla, Anasco, Isabela, Lares, Moca, Rincon, San Sebastian, and Utuado Municipios
349	Includes Arecibo, Camuy, Hatillo, and Quebradillas Municipios
350	Includes Arroyo, Guayama, and Patillas Municipios
351	Includes Hormigueros and Mayaguez Municipios
352	Includes Guanica, Guyanilla, Juana Diaz, Penuelas, Ponce, Villalba, and Yauco Municipios
353	Includes Cabo Rojo, Lajas, Sabana Grande, and San German Municipios
354	Includes Aguas Buenas, Aibonito, Barceloneta, Barranquitas, Bayamon, Caguas, Canovanas, Carolina, Catano, Cayey, Ceiba, Ciales, Cidra, Comerio, Corozal, Dorado, Fajardo, Florida, Guaynabo, Gurabo, Humacao, Juncos, Las Piedras, Loiza, Luquillo, Manati, Maunabo, Morovis, Naguabo, Naranjito, Orocovis, Rio Grande, San Juan, San Lorenzo, Toa Alta, Toa Baja, Trujillo Alto, Vega Alta, Vega Baja, and Yabucoa Municipios

Table 2: FBI's Crime Data, Grouped by Metropolitan Areas, and their Calculated Z-Scores

Crime Rate per 100000 for	**Population**	**Violent Crimes**	**Property Crimes**	**Total Crimes**	**Crime Rate per 100000**	**Number of Violent Crimes**	**Z-Score of Total Crimes**	**Z-Score of Violent Crimes (two weeks)**	**Sum of Z-Scores**	**Z-Score of Safety Rating**

Metropolitan Area					(two weeks)	(two weeks)	(two weeks)			
353	132660	69.4	617.4	686.8	26.415385	2.6692308	-2.1211995	-1.6213094	-3.7425089	-1.882654419
303	155684	81.6	1183.8	1265	48.669231	3.1384615	-1.5796124	-1.5497544	-3.1293669	-1.854634212
118	101545	102.4	1111.8	1214	46.7	3.9384615	-1.6275372	-1.4277591	-3.0552962	-1.774768107
335	135783	89.8	1362.5	1452	55.857692	3.4538462	-1.4046684	-1.5016601	-2.9063285	-1.758922901
14	231052	137.2	1469.8	1607	61.807692	5.2769231	-1.2598645	-1.2236514	-2.4835159	-1.727484432
348	322641	82.1	918	1000	38.465385	3.1576923	-1.8279412	-1.5468219	-3.3747631	-1.639869361
221	2860417	134.4	1385.7	1520	58.465385	5.1692308	-1.3412055	-1.2400738	-2.5812794	-1.574289137
119	128487	111.3	1390.8	1502	57.773077	4.2807692	-1.3580541	-1.3755591	-2.7336132	-1.571762892
242	1954080	126	1518.8	1645	63.261538	4.8461538	-1.2244826	-1.2893412	-2.5138238	-1.564129683
220	396951	173.3	1262.9	1436	55.238462	6.6653846	-1.4197385	-1.011919	-2.4316575	-1.562618022
98	152068	92.1	1323.1	1415	54.430769	3.5423077	-1.4393951	-1.4881702	-2.9275653	-1.529136767
163	135985	113.2	1815.6	1929	74.184615	4.3538462	-0.95865	-1.3644153	-2.3230653	-1.523662102
292	114823	162.9	1720	1883	72.419231	6.2653846	-1.0016138	-1.0729167	-2.0745305	-1.517363513
62	629627	174.7	1420.5	1595	61.353846	6.7192308	-1.2709097	-1.0037078	-2.2746174	-1.505569832
233	170212	169.8	1665	1835	70.569231	6.5307692	-1.0466368	-1.0324471	-2.0790839	-1.504112645
202	84059	123.7	1239.6	1363	52.434615	4.7576923	-1.4879751	-1.3028311	-2.7908061	-1.479088522
173	135898	153.8	1592.4	1746	67.161538	5.9153846	-1.1295691	-1.1262897	-2.2558588	-1.446649088
262	213400	141	1381	1522	58.538462	5.4230769	-1.3394271	-1.2013638	-2.5407908	-1.438866075
315	111413	189.4	1007.1	1197	46.019231	7.2846154	-1.6441049	-0.9174899	-2.5615948	-1.422993632
111	101856	199.3	1567.9	1767	67.969231	7.6653846	-1.1099125	-0.8594248	-1.9693372	-1.408551138
131	130160	140.6	1415.2	1556	59.838462	5.4076923	-1.3077892	-1.2037098	-2.5114991	-1.407883828
24	153425	76.9	2259.7	2337	89.869231	2.9576923	-0.5769368	-1.5773207	-2.1542575	-1.402967525
160	180937	167.5	1622.1	1790	68.830769	6.4423077	-1.0889454	-1.045937	-2.1348823	-1.372209984
331	1272900	184.1	1608.1	1792	68.930769	7.0807692	-1.0865117	-0.9485752	-2.0350869	-1.36567307
96	165411	131.2	1737.5	1869	71.873077	5.0461538	-1.0149054	-1.2588424	-2.2737477	-1.346641119
150	139742	165.3	1730.3	1896	72.907692	6.3576923	-0.9897262	-1.0588403	-2.0485665	-1.332484615
304	119879	147.6	1698.4	1846	71	5.6769231	-1.0361533	-1.1626537	-2.198807	-1.316932208
57	225461	161.9	1781.2	1943	74.734615	6.2269231	-0.9452647	-1.0787819	-2.0240466	-1.288918809
10	93310	131.8	1762.9	1895	72.873077	5.0692308	-0.9905686	-1.2553233	-2.2458919	-1.280734049
190	99371	234.5	1474.3	1709	65.723077	9.0192308	-1.1645766	-0.652971	-1.8175477	-1.277451973
64	870131	166.1	1682.9	1849	71.115385	6.3884615	-1.0333452	-1.0541482	-2.0874934	-1.268490954
167	531837	165.1	1576.8	1742	66.996154	6.35	-1.133594	-1.0600133	-2.1936074	-1.253946321
8	126112	233.1	1643	1876	72.157692	8.9653846	-1.0079788	-0.6611823	-1.669161	-1.246701242

248	522033	127.6	1999.5	2127	81.811538	4.9076923	-0.7730352	-1.2799569	-2.0529921	-1.216256928
345	439739	205.1	1671.2	1876	72.165385	7.8884615	-1.0077916	-0.8254068	-1.8331984	-1.208773524
78	87222	120.4	2544.1	2665	102.48077	4.6307692	-0.2700125	-1.3221861	-1.5921986	-1.195148145
140	138893	154.8	1763.9	1919	73.796154	5.9538462	-0.9681039	-1.1204245	-2.0885284	-1.191961399
334	120437	181.8	1983.6	2165	83.284615	6.9923077	-0.7371852	-0.9620651	-1.6992503	-1.175980007
306	150723	134.7	1734.3	1869	71.884615	5.1807692	-1.0146246	-1.2383143	-2.2529389	-1.171315647
210	137326	201.7	1594	1796	69.065385	7.7576923	-1.0832356	-0.8453484	-1.928584	-1.160277796
49	54298	294.7	1611.5	1906	73.315385	11.334615	-0.9798042	-0.2998882	-1.2796925	-1.159624105
188	632961	208.5	2037.9	2246	86.4	8.0192308	-0.6613668	-0.8054653	-1.466832	-1.15452395
100	88535	179.6	2237.5	2417	92.965385	6.9076923	-0.5015864	-0.9749685	-1.4765549	-1.153700027
112	321817	191.7	2152.5	2344	90.161538	7.3730769	-0.569823	-0.904	-1.473823	-1.102916379
352	325929	238.7	943.2	1182	45.457692	9.1807692	-1.6577709	-0.6283374	-2.2861083	-1.096256898
35	180931	189.6	1698.4	1888	72.615385	7.2923077	-0.99684	-0.9163169	-1.9131569	-1.092103234
350	80581	197.3	1258.4	1456	55.988462	7.5884615	-1.4014859	-0.8711551	-2.272641	-1.089508896
82	198874	199.1	2144.6	2344	90.142308	7.6576923	-0.570291	-0.8605978	-1.4308888	-1.088896061
148	150805	236.1	1953.5	2190	84.215385	9.0807692	-0.7145333	-0.6435868	-1.3581201	-1.078852365
90	2533067	213.7	1471.6	1685	64.819231	8.2192308	-1.1865733	-0.7749664	-1.9615398	-1.058131711
31	168749	168.3	2359.1	2527	97.207692	6.4730769	-0.3983423	-1.0412448	-1.4395871	-1.051465421
261	312777	202.7	2251.8	2455	94.403846	7.7961538	-0.4665789	-0.8394832	-1.3060621	-1.050811729
52	152602	148.8	2026.2	2175	83.653846	5.7230769	-0.7281993	-1.1556155	-1.8838148	-1.050369126
339	116875	218.2	1902.9	2121	81.580769	8.3923077	-0.7786514	-0.7485732	-1.5272245	-1.033992795
186	257560	229.1	1647	1876	72.157692	8.8115385	-1.0079788	-0.6846429	-1.6926217	-1.031732113
7	828360	182.8	1947.8	2131	81.946154	7.0307692	-0.7697591	-0.9562	-1.725959	-1.023738012
142	163631	259.7	1812	2072	79.680769	9.9884615	-0.8248912	-0.5051689	-1.3300602	-1.021906314
336	114491	117	2063.9	2181	83.880769	4.5	-0.7226767	-1.3421277	-2.0648044	-1.015893716
337	145171	283.1	1714.5	1998	76.830769	10.888462	-0.8942511	-0.3679241	-1.2621752	-1.013973497
349	191864	153.2	1418.7	1572	60.457692	5.8923077	-1.2927192	-1.1298088	-2.4225279	-1.009104858
50	81960	184.2	2380.4	2565	98.638462	7.0846154	-0.3635219	-0.9479887	-1.3115107	-1.00775662
38	663371	228.2	1772.2	2000	76.938462	8.7769231	-0.8916302	-0.6899216	-1.5815518	-1.005577649
92	96347	177.5	1793.5	1971	75.807692	6.8269231	-0.9191495	-0.9872853	-1.9064348	-0.990937686
45	110842	237.3	1994.7	2232	85.846154	9.1269231	-0.6748456	-0.6365486	-1.3113942	-0.961439863
36	192070	273.3	1780.6	2054	78.996154	10.511538	-0.8415526	-0.4254027	-1.2669553	-0.94347016
286	561534	226.5	2047.6	2274	87.465385	8.7115385	-0.6354387	-0.6998923	-1.3353311	-0.93794102
59	96236	160	2432.6	2593	99.715385	6.1538462	-0.3373131	-1.0899257	-1.4272388	-0.929170661
305	192150	178.5	2318.5	2497	96.038462	6.8653846	-0.4267976	-0.9814202	-1.4082177	-0.921966438

246	2361431	287.2	1819.6	2107	81.030769	11.046154	-0.7920366	-0.343877	-1.1359135	-0.915075441
228	629218	155	2084	2239	86.115385	5.9615385	-0.6682934	-1.1192515	-1.7875449	-0.910295323
130	559478	237.9	1903.2	2141	82.35	9.15	-0.7599307	-0.6330295	-1.3929602	-0.909144554
234	116963	128.2	2387.1	2515	96.742308	4.9307692	-0.4096682	-1.2764379	-1.6861061	-0.897459821
341	132823	176.2	2114.8	2291	88.115385	6.7769231	-0.6196198	-0.99491	-1.6145299	-0.896683562
175	107711	142	2145.6	2288	87.984615	5.4615385	-0.6228023	-1.1954986	-1.8183009	-0.883957009
191	99160	179.5	2184.3	2364	90.915385	6.9038462	-0.5514768	-0.975555	-1.5270318	-0.877140914
351	98661	178.4	1650.1	1829	70.326923	6.8615385	-1.0525338	-0.9820067	-2.0345405	-0.857700405
39	164892	157.1	2319.7	2477	95.261538	6.0423077	-0.4457054	-1.1069346	-1.55264	-0.851347342
182	3156440	198.2	1734.7	1933	74.342308	7.6230769	-0.9548122	-0.8658765	-1.8206887	-0.839049774
290	144091	281.8	2202.1	2484	95.534615	10.838462	-0.4390596	-0.3755488	-0.8146084	-0.817334964
117	190345	176.5	1952.8	2129	81.896154	6.7884615	-0.7709759	-0.9931505	-1.7641264	-0.803668728
41	927225	244.6	1606.2	1851	71.184615	9.4076923	-1.0316603	-0.5937329	-1.6253932	-0.799092889
4	881039	267.9	2222	2490	95.765385	10.303846	-0.4334434	-0.4570746	-0.890518	-0.794203822
189	405230	267	2075.1	2342	90.080769	10.269231	-0.5717887	-0.4623532	-1.0341419	-0.794176586
278	261200	173.8	1747.7	1922	73.903846	6.6846154	-0.965483	-1.0089864	-1.9744694	-0.786563805
253	167298	262.4	2570.9	2833	108.97308	10.092308	-0.1120106	-0.489333	-0.6013436	-0.766047428
121	101602	206.7	2187	2394	92.065385	7.95	-0.5234895	-0.8160226	-1.3395121	-0.76097451
201	111335	166.2	2608.3	2775	106.71154	6.3923077	-0.1670492	-1.0535617	-1.2206109	-0.75727026
125	275436	287.2	2023.7	2311	88.880769	11.046154	-0.6009928	-0.343877	-0.9448698	-0.750651635
12	356841	285	1843.1	2128	81.85	10.961538	-0.7720991	-0.3567803	-1.1288795	-0.729222815
320	297852	259.2	2093.3	2353	90.480769	9.9692308	-0.562054	-0.5081015	-1.0701555	-0.725600275
101	843273	368.7	2029.7	2398	92.246154	14.180769	-0.5190902	0.13413381	-0.3849564	-0.719315305
147	160897	233.1	2503.5	2737	105.25385	8.9653846	-0.2025247	-0.6611823	-0.863707	-0.713220996
149	202004	288.6	2465.3	2754	105.91923	11.1	-0.1863314	-0.3356657	-0.5219972	-0.698873831
256	413879	327.6	1774.4	2102	80.846154	12.6	-0.7965295	-0.1069244	-0.9034539	-0.679474178
235	847935	222.9	1982.7	2206	84.830769	8.5730769	-0.6995568	-0.7210069	-1.4205637	-0.674169745
157	276409	205.1	2213	2418	93.003846	7.8884615	-0.5006504	-0.8254068	-1.3260572	-0.670908099
84	153346	166.9	2445.5	2612	100.47692	6.4192308	-0.3187797	-1.0494561	-1.3682357	-0.670233978
137	210453	242.3	2875.2	3118	119.90385	9.3192308	0.1540091	-0.6072228	-0.4532136	-0.663921772
33	247250	251.2	2526.6	2778	106.83846	9.6615385	-0.1639603	-0.5550228	-0.7189831	-0.660619268
259	1255599	232.2	2325.9	2558	98.388462	8.9307692	-0.3696061	-0.6664609	-1.0360671	-0.659495736
241	1256578	275.8	2080.4	2356	90.623077	10.607692	-0.5585906	-0.4107398	-0.9693305	-0.635949229
284	500416	363.9	1715.2	2079	79.965385	13.996154	-0.8179646	0.10598103	-0.7119836	-0.630597131
34	126444	338.5	2125.1	2464	94.753846	13.019231	-0.458061	-0.0429941	-0.5010551	-0.6167879

254	194990	199	2278.6	2478	95.292308	7.6538462	-0.4449566	-0.8611843	-1.3061409	-0.602536067
343	856152	421	1874.2	2295	88.276923	16.192308	-0.6156885	0.44088183	-0.1748067	-0.587126655
215	142015	376	1679.4	2055	79.053846	14.461538	-0.8401485	0.1769495	-0.663199	-0.583722012
80	100807	258.9	2795.4	3054	117.47308	9.9576923	0.0948521	-0.5098611	-0.415009	-0.582441867
263	1085775	259	2247.5	2507	96.403846	9.9615385	-0.4179053	-0.5092746	-0.9271799	-0.573140384
75	80345	109.5	3202.4	3312	127.38077	4.2115385	0.3359735	-1.3861164	-1.0501429	-0.569456559
311	662707	279.3	2284.9	2564	98.623077	10.742308	-0.3638964	-0.3902117	-0.7541081	-0.55735646
104	227885	251.9	2175.7	2428	93.369231	9.6884615	-0.4917581	-0.5509172	-1.0426753	-0.557015995
164	210988	218.5	2457	2676	102.90385	8.4038462	-0.2597162	-0.7468136	-1.0065298	-0.553686255
218	128067	233.5	2440.1	2674	102.83077	8.9807692	-0.2614946	-0.6588362	-0.9203309	-0.543567657
51	263979	209.1	2450.6	2660	102.29615	8.0423077	-0.2745055	-0.8019462	-1.0764516	-0.535130954
19	153664	252.5	2561.4	2814	108.22692	9.7115385	-0.1301696	-0.5473981	-0.6775677	-0.532870271
159	308581	318.2	2523.8	2842	109.30769	12.238462	-0.1038672	-0.1620569	-0.2659241	-0.526476352
247	129547	307.2	2127.4	2435	93.638462	11.815385	-0.4852059	-0.2265737	-0.7117796	-0.518434587
95	166423	218.1	2436	2654	102.08077	8.3884615	-0.2797472	-0.7491597	-1.028907	-0.507110746
114	426293	229.7	2446.7	2676	102.93846	8.8346154	-0.2588738	-0.6811238	-0.9399976	-0.505027105
216	346776	396.2	2119.2	2515	96.746154	15.238462	-0.4095746	0.29542579	-0.1141488	-0.504489172
3	51889	97.7	3188.7	3286	126.4	3.7576923	0.3121047	-1.4553253	-1.1432206	-0.503093268
107	138202	348	3184.5	3533	135.86538	13.384615	0.5424617	0.01272494	0.5551867	-0.503059221
250	444898	331.3	2183	2514	96.703846	12.742308	-0.4106043	-0.0852233	-0.4958275	-0.502317008
330	6031640	316.6	2111.6	2428	93.392308	12.176923	-0.4911965	-0.1714412	-0.6626376	-0.501227524
124	82773	247.7	3288.5	3536	136.00769	9.5269231	0.5459250	-0.5755509	-0.0296259	-0.501016435
293	123565	271.9	2150.3	2422	93.161538	10.457692	-0.4968126	-0.433614	-0.9304266	-0.500675971
132	1024517	252.2	2232.2	2484	95.553846	9.7	-0.4385916	-0.5491577	-0.9877492	-0.493798593
226	341542	415.2	2028.4	2444	93.984615	15.969231	-0.4767816	0.40686388	-0.0699177	-0.475025395
27	106711	277.4	1990.4	2268	87.223077	10.669231	-0.6413357	-0.4013556	-1.0426913	-0.472703428
294	169008	240.2	2635.4	2876	110.6	9.2384615	-0.0724165	-0.6195396	-0.6919562	-0.472410629
206	112637	269	2899.6	3169	121.86923	10.346154	0.2018403	-0.4506229	-0.2487826	-0.465846477
15	441690	205.6	2308.9	2515	96.711538	7.9076923	-0.4104171	-0.8224742	-1.2328913	-0.465540061
211	115787	383.5	2695.5	3079	118.42308	14.75	0.1179720	0.22093822	0.3389102	-0.462986579
225	146061	339.6	2378.5	2718	104.54231	13.061538	-0.2198413	-0.0365424	-0.2563837	-0.462251175
280	279628	420.9	2032.3	2453	94.353846	16.188462	-0.4677957	0.44029531	-0.0275004	-0.435783484
81	142646	221.5	2742.5	2964	114	8.5192308	0.0103285	-0.7292182	-0.7188896	-0.427517012
239	382542	309.2	2352.2	2661	102.36154	11.892308	-0.2729142	-0.2148434	-0.4877576	-0.427013125
37	163976	264.1	2446.7	2711	104.26154	10.157692	-0.2266743	-0.4793622	-0.7060365	-0.416935383

83	384694	355.3	2427.9	2783	107.04615	13.665385	-0.1589057	0.05554063	-0.1033651	-0.411896514
174	62666	188.3	2992.1	3180	122.32308	7.2423077	0.2128855	-0.9239416	-0.7110561	-0.403657277
85	108808	364.9	2432.7	2798	107.6	14.034615	-0.1454269	0.11184619	-0.0335807	-0.400409249
205	3491062	261.8	2496.5	2758	106.08846	10.069231	-0.1822129	-0.4928521	-0.675065	-0.391073719
251	1610481	328.9	2133.3	2462	94.7	12.65	-0.4593714	-0.0992997	-0.5586711	-0.390488121
70	240441	292.4	2506.2	2799	107.63846	11.246154	-0.1444909	-0.3133781	-0.457869	-0.385789714
99	201503	357.3	2149.3	2507	96.407692	13.742308	-0.4178117	0.06727095	-0.3505407	-0.383243041
143	160565	412.3	2144.3	2557	98.330769	15.857692	-0.3710102	0.38985491	0.0188447	-0.375786875
25	215384	425.8	2000.1	2426	93.303846	16.376923	-0.4933493	0.46903461	-0.0243147	-0.370216879
325	1715279	308.6	2782.8	3091	118.9	11.869231	0.1295788	-0.2183625	-0.0887837	-0.35877047
177	317498	301.4	3048.8	3350	128.85385	11.592308	0.3718234	-0.2605916	0.1112318	-0.353554558
93	280297	224.4	3151.3	3376	129.83462	8.6307692	0.3956922	-0.7122092	-0.316517	-0.34943494
295	247531	327.6	2278.9	2607	100.25	12.6	-0.3243023	-0.1069244	-0.4312267	-0.335503145
162	82820	227	2790.4	3017	116.05385	8.7307692	0.0603126	-0.6969598	-0.6366472	-0.334665602
42	422772	259	3316.7	3576	137.52692	9.9615385	0.5828982	-0.5092746	0.0736237	-0.333773585
69	146681	276.1	2638.4	2915	112.09615	10.619231	-0.036005	-0.4089803	-0.4449852	-0.322715307
203	161969	322.3	2580.1	2902	111.63077	12.396154	-0.0473309	-0.1380097	-0.1853407	-0.309171639
122	84623	202.1	3177.6	3380	129.98846	7.7730769	0.3994363	-0.8430023	-0.443566	-0.284726305
87	608260	316.8	2498.6	2815	108.28462	12.184615	-0.1287656	-0.1702681	-0.2990337	-0.283575535
227	95711	238.2	3694.5	3933	151.25769	9.1615385	0.9170610	-0.6312699	0.2857911	-0.283418923
123	148670	349.1	2617.2	2966	114.08846	13.426923	0.0124814	0.01917662	0.0316580	-0.283017175
274	3256669	325.2	1813.5	2139	82.257692	12.507692	-0.7621772	-0.1210008	-0.883178	-0.281668936
332	4758740	352	2246.3	2598	99.934615	13.538462	-0.3319777	0.03618559	-0.2957921	-0.269337322
222	2506630	316	1594.7	1911	73.488462	12.153846	-0.9755921	-0.1749603	-1.1505524	-0.259906462
133	363897	193.7	2746.7	2940	113.09231	7.45	-0.0117618	-0.8922697	-0.9040315	-0.257455118
155	111679	313.4	2612	2925	112.51538	12.053846	-0.0258022	-0.1902097	-0.2160119	-0.239383276
268	404329	212.5	3101.4	3314	127.45769	8.1730769	0.3378455	-0.7820046	-0.4441591	-0.228182002
91	171672	422.9	2737.2	3160	121.54231	16.265385	0.1938841	0.45202564	0.6459097	-0.225887273
21	1938280	290.9	2878.8	3170	121.91154	11.188462	0.2028699	-0.3221759	-0.1193059	-0.22562852
354	2242285	283.5	1425.4	1709	65.726923	10.903846	-1.164483	-0.3655781	-1.5300611	-0.213446709
60	9546349	380.1	2135.4	2516	96.75	14.619231	-0.409481	0.20099667	-0.2084844	-0.206405909
317	371608	347.1	1816.2	2163	83.203846	13.35	-0.7391509	0.00744629	-0.7317046	-0.204104371
30	208491	202.9	3425.6	3629	139.55769	7.8038462	0.6323206	-0.8383102	-0.2059896	-0.195851516
53	235685	462.9	2305.2	2768	106.46538	17.803846	-0.1730398	0.68663215	0.5135924	-0.193713401
134	202116	435.4	2607.4	3043	117.03077	16.746154	0.0840877	0.52534017	0.6094279	-0.151584354

255	143222	382.6	2462.6	2845	109.43077	14.715385	-0.1008719	0.21565957	0.1147877	-0.149752657
230	265955	226	2739.6	2966	114.06154	8.6923077	0.0118262	-0.7028249	-0.6909987	-0.140621405
72	172934	342.3	2974	3316	127.55	13.165385	0.3400920	-0.0207065	0.3193855	-0.136454123
321	144114	263.7	3382.7	3646	140.24615	10.142308	0.6490756	-0.4817083	0.1673673	-0.131653577
283	441058	293.4	2060.5	2354	90.534615	11.284615	-0.5607435	-0.307513	-0.8682565	-0.124728534
168	468547	424.3	1994	2418	93.011538	16.319231	-0.5004632	0.46023686	-0.0402263	-0.115678995
46	404136	287	2692.4	2979	114.59231	11.038462	0.0247434	-0.34505	-0.3203066	-0.115154679
135	81944	346.6	2697	3044	117.06154	13.330769	0.0848365	0.00451371	0.0893503	-0.093017694
213	117526	280.8	2967.9	3249	124.95	10.8	0.2768163	-0.381414	-0.1045977	-0.085554717
67	276035	460.1	2507.7	2968	114.14615	17.696154	0.0138855	0.67020969	0.6840951	-0.074026598
48	97805	399.8	2724.8	3125	120.17692	15.376923	0.1606550	0.31654038	0.4771954	-0.073100535
194	210715	315.1	3935.2	4250	163.47308	12.119231	1.2143442	-0.1802389	1.0341053	-0.06524943
56	2370253	392.2	2822.1	3214	123.62692	15.084615	0.2446169	0.27196514	0.5165820	-0.057275756
249	2345482	258.7	2898.3	3157	121.42308	9.95	0.1909824	-0.5110341	-0.3200517	-0.055518961
169	267304	402.5	3750	4153	159.71154	15.480769	1.1228005	0.33237631	1.4551768	-0.045257369
328	63981	201.6	3532.3	3734	143.61154	7.7538462	0.7309782	-0.8459349	-0.1149567	-0.044392589
16	199695	300.5	2883.4	3184	122.45769	11.557692	0.2161616	-0.2658703	-0.0497087	-0.035295385
66	2145462	267.3	2957.9	3225	124.04615	10.280769	0.2548196	-0.4605937	-0.2057741	-0.026198179
18	276587	384	2937.6	3322	127.75385	14.769231	0.3450529	0.2238708	0.5689238	-0.008262523
193	831477	329.4	3365.3	3695	142.10385	12.669231	0.6942858	-0.0963671	0.5979187	-0.005416242
158	430225	341.2	2765.3	3107	119.48077	13.123077	0.1437128	-0.0271582	0.1165547	0.000861919
61	7341262	427	2193.5	2621	100.78846	16.423077	-0.3111979	0.4760728	0.1648750	0.006486388
44	155421	371.9	2768	3140	120.76538	14.303846	0.1749763	0.15290233	0.3278786	0.008542793
223	155008	427.1	2379.9	2807	107.96154	16.426923	-0.1366282	0.47665932	0.3400311	0.010108928
105	125309	534.7	1983.1	2518	96.838462	20.565385	-0.4073282	1.10775084	0.7004227	0.03390738
219	807947	326.6	2666.5	2993	115.11923	12.561538	0.0375670	-0.1127895	-0.0752225	0.040607716
63	705329	339.1	2727.8	3067	117.95769	13.042308	0.1066460	-0.039475	0.0671710	0.051849846
179	218568	344.1	2965.7	3310	127.3	13.234615	0.3340078	-0.0101492	0.3238586	0.060306977
165	205249	205.1	3158.6	3364	129.37308	7.8884615	0.3844598	-0.8254068	-0.440947	0.065890591
127	176019	413.6	3123.5	3537	136.04231	15.907692	0.5467675	0.39747962	0.9442471	0.07857629
102	315179	291.6	3262.3	3554	136.68846	11.215385	0.5624928	-0.3180702	0.2444225	0.079386594
333	170225	480	2383.9	2864	110.15	18.461538	-0.0833681	0.78692643	0.7035583	0.083124892
40	255676	272.6	2887.2	3160	121.53077	10.484615	0.1936033	-0.4295083	-0.2359051	0.088831073
291	98122	317	2912.7	3230	124.21923	12.192308	0.2590318	-0.1690951	0.0899367	0.094557682
170	213753	285.8	3050.7	3337	128.32692	10.992308	0.3589998	-0.3520882	0.0069116	0.100931172

126	746709	320.9	3066.1	3387	130.26923	12.342308	0.4062693	-0.146221	0.2600483	0.114672311
110	147427	340.5	2807.5	3148	121.07692	13.096154	0.1825581	-0.0312638	0.1512943	0.11657891
129	151437	459.6	2294.7	2754	105.93462	17.676923	-0.185957	0.66727711	0.4813201	0.128876477
240	6054007	459.6	2331.3	2791	107.34231	17.676923	-0.1516983	0.66727711	0.5155788	0.136938673
79	260307	498.6	2938.5	3437	132.19615	19.176923	0.4531644	0.89601846	1.3491829	0.137149759
308	2807175	429.8	2449.2	2879	110.73077	16.530769	-0.069234	0.49249526	0.4232612	0.139471726
323	99086	429.9	2887.4	3317	127.58846	16.534615	0.3410280	0.49308178	0.8341098	0.149692463
181	13277942	368.9	2050.4	2419	93.05	14.188462	-0.4995271	0.13530684	-0.3642203	0.150175923
55	727099	392.9	2895.1	3288	126.46154	15.111538	0.3136023	0.27607075	0.5896731	0.153069868
113	279713	424.7	3103.5	3528	135.7	16.334615	0.5384368	0.46258293	1.0010197	0.180075492
258	444810	378.8	2394.7	2774	106.67308	14.569231	-0.1679852	0.19337196	0.0253867	0.190241755
161	858559	391.5	3136.3	3528	135.68462	15.057692	0.5380624	0.26785952	0.8059219	0.190983968
47	677068	439.4	2586	3025	116.36154	16.9	0.0678008	0.54880082	0.6166016	0.194626935
154	333814	456.2	2517.6	2974	114.37692	17.546154	0.0195016	0.64733556	0.6668372	0.194817594
270	389229	413.6	3231.3	3645	140.18846	15.907692	0.6476715	0.39747962	1.0451511	0.200551013
217	1783924	610.9	2567	3178	122.22692	23.496154	0.2105454	1.55467625	1.7652217	0.202083101
347	203851	372.3	2558.2	2931	112.71154	14.319231	-0.0210285	0.1552484	0.1342199	0.20943032
136	139880	528.3	2663.7	3192	122.76923	20.319231	0.2237434	1.0702138	1.2939572	0.228312468
212	119835	206.1	3666.7	3873	148.95385	7.9269231	0.8609928	-0.8195417	0.0414511	0.290324627
282	147809	272.6	2823.9	3097	119.09615	10.484615	0.1343525	-0.4295083	-0.2951558	0.299237982
327	262172	384.5	3076.6	3461	133.11923	14.788462	0.4756292	0.22680338	0.7024325	0.302097881
236	556949	560.4	3011.2	3572	137.36923	21.553846	0.5790605	1.25848553	1.8375460	0.305529761
86	608127	461.1	3234.9	3696	142.15385	17.734615	0.6955027	0.67607486	1.3715775	0.326216368
244	721696	501.5	2922	3424	131.67308	19.288462	0.4404344	0.91302744	1.3534619	0.328177442
296	318782	323.4	2827	3150	121.16923	12.438462	0.1848046	-0.1315581	0.0532465	0.348128647
120	125267	368.8	3387.2	3756	144.46154	14.184615	0.7516645	0.13472033	0.8863848	0.360739444
297	321808	394.3	3026	3420	131.55	15.165385	0.4374391	0.28428198	0.7217211	0.375045751
267	195891	660.1	1947.5	2608	100.29231	25.388462	-0.3232726	1.84324226	1.5199696	0.389644858
29	124037	375.7	3011.2	3387	130.26538	14.45	0.4061757	0.17518995	0.5813657	0.392586471
176	105180	386	3296.3	3682	141.62692	14.846154	0.6826791	0.23560113	0.9182802	0.393635099
151	126640	412.2	3541.5	3954	152.06538	15.853846	0.9367177	0.38926839	1.3259861	0.395977493
272	118519	293.6	3562.3	3856	148.30385	11.292308	0.8451739	-0.3063399	0.5388340	0.398823776
68	119510	494.5	3419	3914	150.51923	19.019231	0.8990892	0.8719713	1.7710605	0.427504484
198	1875917	418.6	3102.5	3521	135.42692	16.1	0.5317909	0.42680544	0.9585964	0.431998612
329	188330	348.9	4107.7	4457	171.40769	13.419231	1.4074472	0.01800359	1.4254508	0.439488825

313	2914610	447.5	3236.4	3684	141.68846	17.211538	0.6841767	0.59630864	1.2804853	0.443131794
265	150531	453.1	2986.1	3439	132.27692	17.426923	0.4551301	0.62915355	1.0842836	0.444650264
279	1950374	249.8	2246.7	2497	96.019231	9.6076923	-0.4272656	-0.5632341	-0.9904997	0.44583508
71	689470	385.8	2883.2	3269	125.73077	14.838462	0.2958177	0.2344281	0.5302458	0.451119084
76	1985491	294.9	3097.9	3393	130.49231	11.342308	0.4116983	-0.2987152	0.1129830	0.453216343
300	629676	507.4	2525.3	3033	116.64231	19.515385	0.0746338	0.9476319	1.0222657	0.454802907
183	10121502	422.1	2148.8	2571	98.880769	16.234615	-0.357625	0.44733351	0.0897085	0.459800922
266	2243875	410.6	2474.9	2886	110.98077	15.792308	-0.0631498	0.37988413	0.3167342	0.462674441
346	170005	360	2646.4	3006	115.63077	13.846154	0.0500162	0.08310689	0.1331231	0.472173394
180	102175	247.6	3622.2	3870	148.83846	9.5230769	0.8581847	-0.5761374	0.2820473	0.491539
20	585946	286.9	3304.6	3592	138.13462	11.034615	0.5976875	-0.3456365	0.2520509	0.498790889
319	237088	377.9	3216.5	3594	138.24615	14.534615	0.6004019	0.18809331	0.7884953	0.5036391
32	167246	323.5	3467.9	3791	145.82308	12.442308	0.7847999	-0.1309715	0.6538284	0.5135398
316	234274	368.4	3435.7	3804	146.31154	14.169231	0.7966875	0.13237426	0.9290617	0.534178744
26	61225	537.5	2708.3	3246	124.83846	20.673077	0.2741018	1.1241733	1.3982751	0.543909212
224	745917	542.8	3348	3891	149.64615	20.876923	0.8778413	1.15525866	2.0331000	0.554490841
184	1269992	395	3289.4	3684	141.70769	15.192308	0.6846447	0.28838759	0.9730323	0.567789374
65	223878	302.8	2961.9	3265	125.56538	11.646154	0.2917928	-0.2523804	0.0394124	0.57335937
214	170933	445.2	3555.2	4000	153.86154	17.123077	0.9804302	0.58281877	1.5632490	0.5741152
97	178032	339.3	3201.1	3540	136.16923	13.05	0.5498563	-0.038302	0.5115543	0.578942983
338	152243	343.5	3409	3753	144.32692	13.211538	0.7483883	-0.0136683	0.7347200	0.583750339
285	371693	354.1	3176.3	3530	135.78462	13.619231	0.5404960	0.04850243	0.5889984	0.590042118
187	153544	578.3	2201.3	2780	106.90769	22.242308	-0.1622754	1.36347194	1.2011965	0.594263874
139	440192	477.7	3174.1	3652	140.45385	18.373077	0.6541301	0.77343656	1.4275666	0.619267569
153	162229	313.1	3575.2	3888	149.55	12.042308	0.8755012	-0.1919692	0.6835320	0.628051548
166	633015	452.9	3292.5	3745	144.05385	17.419231	0.7417425	0.62798052	1.3697230	0.638422088
281	272480	418	2980.4	3398	130.70769	16.076923	0.4169400	0.42328634	0.8402264	0.639858847
28	408113	494	2972.2	3466	133.31538	19	0.4804029	0.86903871	1.3494416	0.658039638
326	459432	421.6	2486.5	2908	111.85	16.215385	-0.0419956	0.44440092	0.4024053	0.659204025
237	193811	500	3834.7	4335	166.71923	19.230769	1.2933451	0.90422969	2.1975748	0.676901357
340	272484	406.3	3400.6	3807	146.41923	15.626923	0.7993084	0.35466393	1.1539723	0.697649249
43	114492	420.1	4155.7	4576	175.99231	16.157692	1.5190220	0.43560318	1.9546252	0.702429368
307	128038	346	4001.2	4347	167.2	13.307692	1.3050455	0.00099461	1.3060401	0.704090834
146	1417629	561.1	3432.8	3994	153.61154	21.580769	0.9743460	1.26259114	2.2369372	0.716790151
54	223677	499.4	3606.5	4106	157.91923	19.207692	1.0791814	0.90071059	1.9798920	0.72497491

260	4440461	327.5	2617.1	2945	113.25385	12.596154	-0.0078305	-0.1075109	-0.1153414	0.743966007
231	903607	364.9	3128.7	3494	134.36923	14.034615	0.5060501	0.11184619	0.6178963	0.744558414
342	654625	402.8	3537.4	3940	151.54615	15.492308	0.9240812	0.33413586	1.2582171	0.755780115
152	175290	328.6	4260.9	4590	176.51923	12.638462	1.5318456	-0.1010592	1.4307864	0.768847135
116	274003	661.3	3223.7	3885	149.42308	25.434615	0.8724123	1.85028046	2.7226928	0.769820862
94	542584	426.7	3258.7	3685	141.74615	16.411538	0.6855807	0.47431326	1.159894	0.777603876
144	577909	363.9	2998.7	3363	129.33077	13.996154	0.3834301	0.10598103	0.4894112	0.810356537
88	4299979	529.4	2203.7	2733	105.11923	20.361538	-0.2058008	1.07666548	0.8708646	0.810942135
23	2790201	588.5	2793.5	3382	130.07692	22.634615	0.4015891	1.4232966	1.8248857	0.812256326
17	5597635	398.4	3231.3	3630	139.60385	15.323077	0.6334438	0.30832915	0.9417730	0.864817198
264	343135	664.8	2868.8	3534	135.90769	25.569231	0.5434913	1.87080853	2.4142998	0.869583698
196	266350	557.5	2675.4	3233	124.34231	21.442308	0.2620270	1.24147655	1.5035036	0.883855958
344	248862	243.1	3291.4	3535	135.94231	9.35	0.5443337	-0.6025306	-0.0581969	0.890168166
200	1395570	527	3417.3	3944	151.70385	20.269231	0.9279189	1.06258909	1.9905080	0.912454955
1	169202	400.1	3668.4	4069	156.48077	15.388462	1.0441739	0.31829992	1.3624738	0.937451841
192	121351	211.8	4554.6	4766	183.32308	8.1461538	1.6974294	-0.7861102	0.9113191	0.961168581
73	803559	585.5	3411.9	3997	153.74615	22.519231	0.9776221	1.40570111	2.3833232	0.961829082
145	131143	755.7	3137	3893	149.71923	29.065385	0.8796198	2.40395183	3.2835716	0.963674399
324	157616	511.4	3886	4397	169.13077	19.669231	1.3520342	0.97109255	2.3231268	0.973193779
299	211855	767	3299.9	4067	156.41923	29.5	1.0426762	2.47022817	3.5129044	0.982004994
58	546512	532.8	3741.7	4275	164.40385	20.492308	1.2369961	1.09660703	2.3336031	0.984374624
108	413377	652.2	2733.8	3386	130.23077	25.084615	0.4053332	1.79690748	2.2022407	1.027545493
77	449583	589.4	4084.9	4674	179.78077	22.669231	1.6112210	1.42857525	3.0397962	1.04717666
13	116381	617.8	3347.6	3965	152.51538	23.761538	0.9476692	1.59514587	2.5428150	1.093636413
156	2066584	482.1	3017.2	3499	134.58846	18.542308	0.5113855	0.79924328	1.3106287	1.111177131
273	2326684	404.9	4197.6	4603	177.01923	15.573077	1.5440140	0.34645271	1.8904667	1.158406332
209	373331	394	3612.1	4006	154.08077	15.153846	0.9857656	0.28252243	1.2682880	1.16185183
229	1336996	463.7	3350.8	3815	146.71154	17.834615	0.8064222	0.69132428	1.4977465	1.16338392
318	968064	461	3100.3	3561	136.97308	17.730769	0.5694193	0.67548834	1.2449077	1.180795261
2	155769	612.4	4003.4	4616	177.53077	23.553846	1.5564632	1.56347399	3.1199372	1.193297109
271	1156755	348	4474.8	4823	185.49231	13.384615	1.7502215	0.01272494	1.7629464	1.19557141
269	434416	421.9	2434.8	2857	109.87308	16.226923	-0.0901075	0.44616047	0.3560529	1.233553602
109	207327	521.9	4427.8	4950	190.37308	20.073077	1.8690037	1.03267676	2.9016805	1.234227721
197	5938747	595.2	3888.9	4484	172.46538	22.892308	1.4331880	1.46259319	2.8957812	1.293046325
314	150328	532.8	4079.1	4612	177.38077	20.492308	1.5528127	1.09660703	2.6494197	1.309831212

301	452154	535.9	3916.8	4453	171.25769	20.611538	1.4037967	1.11478904	2.5185857	1.315380781
115	966353	470.6	3373.3	3844	147.84231	18.1	0.8339415	0.7317939	1.5657354	1.393544564
238	474766	672.8	3978.8	4652	178.90769	25.876923	1.5899731	1.91772983	3.5077029	1.404126193
302	135676	367.1	4157	4524	174.00385	14.119231	1.4706293	0.12474955	1.5953788	1.440065599
312	377234	679.2	3660.9	4340	166.92692	26.123077	1.2983997	1.95526687	3.2536666	1.442578226
185	305514	737.8	3953	4691	180.41538	28.376923	1.6266655	2.29896541	3.9256309	1.467418497
207	414522	511.4	4005.8	4517	173.73846	19.669231	1.4641706	0.97109255	2.4352632	1.469277432
138	6454938	567.4	3208.1	3776	145.21154	21.823077	0.7699170	1.29954167	2.0694587	1.470360108
288	2838393	296.5	4266.9	4563	175.51538	11.403846	1.5074152	-0.2893309	1.2180843	1.47823845
106	380427	458.7	4405.8	4865	187.09615	17.642308	1.7892539	0.66199847	2.4512524	1.517432696
277	1608949	521	3736.7	4258	163.75769	20.038462	1.2212708	1.02739811	2.2486689	1.532106704
141	1971378	646.3	3243.4	3890	149.60385	24.857692	0.8768117	1.76230301	2.6391147	1.576387486
287	3667968	327.3	4189.4	4517	173.71923	12.588462	1.4637026	-0.1086839	1.3550187	1.591919465
9	261505	559.8	3838.9	4399	169.18077	21.530769	1.3532511	1.25496643	2.6082175	1.600431071
204	1573272	634	3011.7	3646	140.21923	24.384615	0.6484203	1.69016151	2.3385818	1.6396866
208	531018	532.2	3495	4027	154.89231	20.469231	1.0055158	1.09308793	2.0986038	1.645215739
310	108748	665.8	3763.7	4430	170.36538	25.607692	1.3820808	1.87667369	3.2587545	1.706526541
232	2319802	685.4	4012.5	4698	180.68846	26.361538	1.6333113	1.99163088	3.6249422	1.712212295
172	131086	704.9	3700.6	4406	169.44231	27.111538	1.3596161	2.10600156	3.4656176	1.725715107
257	180406	706.7	3162.3	3869	148.80769	27.180769	0.8574358	2.11655885	2.9739947	1.730025384
178	729360	696.4	4385.2	5082	195.44615	26.784615	1.9924661	2.05614767	4.0486138	1.745366704
275	4585742	498.1	3370	3868	148.77308	19.157692	0.8565934	0.89308588	1.7496793	1.77101728
322	429882	490.6	3129.5	3620	139.23462	18.869231	0.6244579	0.84909716	1.4735551	1.820173509
22	367406	510.5	3233.6	3744	144.00385	19.634615	0.7405257	0.9658139	1.7063396	1.82549837
103	34712	648.2	4007.3	4656	179.05769	24.930769	1.5936236	1.77344682	3.3670705	1.825525608
11	316696	843.7	3951.4	4795	184.42692	32.45	1.7242934	2.92008616	4.6443796	1.831790149
289	829575	432.6	3924.5	4357	167.58077	16.638462	1.3143122	0.50891772	1.8232299	1.97655555
199	2667260	755.1	4688.8	5444	209.38077	29.042308	2.3315899	2.40043273	4.7320226	2.096099358
243	2121653	861.4	3027.3	3889	149.56538	33.130769	0.8758756	3.02389954	3.8997752	2.096896044
6	155023	812.1	4450.3	5262	202.4	31.234615	2.1617004	2.73474701	4.8964474	2.118141014
276	2715593	515.8	3308.7	3825	147.09615	19.838462	0.8157825	0.99689926	1.8126818	2.159486992
171	2066423	743	2791.8	3535	135.95385	28.576923	0.5446145	2.32946426	2.8740788	2.160726282
309	712619	750.2	3521.1	4271	164.28077	28.853846	1.2340008	2.37169343	3.6056942	2.215404842
298	539925	318.6	5414.3	5733	220.49615	12.253846	2.6021026	-0.1597108	2.4423918	2.22189409
245	94694	685.4	3571.5	4257	163.72692	26.361538	1.2205220	1.99163088	3.2121529	2.302073422

5	903982	740.3	4270.5	5011	192.72308	28.473077	1.9261952	2.31362832	4.2398235	2.326048914
74	322951	439.7	5137.6	5577	214.51154	16.911538	2.4564563	0.55056037	3.0070167	2.595655747
128	126481	761.4	5305.9	6067	233.35769	29.284615	2.9151111	2.43738326	5.3524944	2.672593859
195	1348092	1034	4134.6	5168	198.77308	39.75	2.0734327	4.03329407	6.1067268	2.804755272
252	162854	575.4	5105.8	5681	218.50769	22.130769	2.5537098	1.34646297	3.9001728	2.902754502
89	1766912	982.1	3253.2	4235	162.89615	37.773077	1.2003037	3.7318247	4.9321284	3.490286855

Appendix G

Non-Technical Report on the Devised Safety Ranking of My City

For years, criminal activity has been a major issue within several metropolitan cities such as My City. Within the United States, the Federal Bureau of Investigation is responsible for ranking each of the metropolitan cities solely based on what it categorizes as "violent crime," such as murder, robbery, and rape. In an effort to improve the current safety ranking technique employed by My City, we have devised a method to apply the abundant amount of gathered criminal statistics to assess the safeness of cities and metropolitan areas and to suggest optimal distribution of police officers throughout city districts to optimally police the regions. Data regarding FBI crime reports for cities and metropolitan areas across the United States were analyzed in order to develop a system for rating an My City's safeness. Furthermore, a correlation between the criminal activity and the My City's economic prosperity was explored as well as the placement of additional law enforcement in order to improve a city's safeness rating.

In order to rate the safeness of My City in the most accurate manner possible, FBI data was used in conjunction to weighing systems in order to represent the safety as a combined value of the frequency of crime occurrence as well as the severity of the crimes. By using the United States Sentencing Commission's minimum mandatory sentencing guidelines for the crimes described in the FBI report, we were able to weigh more severe crimes i.e. murder and rape more heavily as well as less severe crimes i.e. theft less heavily. The safety rating of My City was calculated to be 1370.9268, whereas the national average safety rating was 1462.467. My City was calculated to be safer than 56.43% of cities and metropolitan areas across the United States.

The model also determined if a significant relationship existed between crime in My City's crime and its economy. To track trends within the past, a city of similar GDP, safety rating, and population was used to be representative for My City in determining the significance

of crime and GDP. Chicago best represented My City due to its safety rating being within +/- 30% of My City's safety rating and the population being within +/- 10% of My City's population. Based on ten years worth of data of the crime and GDP of Chicago, calculations were conducted to determine whether a significant correlation existed between crime and GDP data. It was discovered that there was a significant correlation between the crime and GDP in Chicago, and because of the city's similarity to My City, My City's GDP was then correlated to the crime within My City.

In order to allocate the limited officers within My City's police force efficiently, an allocation strategy was created that determined what proportion of the police force should be assigned to each district. The allocation was optimized by calculating the frequency of violent and property crime in every beat and using the frequencies along with weighting for violent and property crime to determine where to send officers. The model's results stated that districts 3, 4, 6, 7, and 11 had the most dangerous proportions of violent and property crime. As a result, the model suggested that the greatest proportion of My City's police officers ought to patrol the areas with 5.94, 6.63, 6.93, 6.91, and 6.53 percent of the police force, respectively.

Overall, the new safety rating allows My City to determine its safeness in relation to many other United States cities and to represent the violent and property crime with weights that represent severities of each major crime. Also, the versatility of the model allows it to be applied in order to best distribute the police force through My City according to danger in each district.