

For office use only

T1 \_\_\_\_\_

T2 \_\_\_\_\_

T3 \_\_\_\_\_

T4 \_\_\_\_\_

For office use only

F1 \_\_\_\_\_

F2 \_\_\_\_\_

F3 \_\_\_\_\_

F4 \_\_\_\_\_

---

2010

**13th 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: 2671**

**Problem Chosen: B**

Please type a summary of your results on this page. Please remember not to include the name of your school, advisor, or team members on this page.

Crime is an inevitable part of human society. In order to maintain public safety, there have been many attempts at reducing crime rate throughout history through the implementation of policies on both the national and local level. However, Felonia, a small city with an alarming crime rate that has been rising for several years, has no effective crime reduction policies in place. Therefore, it is necessary to determine a method of reducing the dangerous level of crime in Felonia.

Four models were constructed that analyzed the given Felonian public data. Model 1 used multiple linear regression and only the given data to create a representation of the crime rate in Felonia. Models 2 and 3 used the “broken windows” policy and the “three strikes” law, which have been implemented in other regions of the country, respectively to display their potential positive effects on Felonian violent crime rate. Model 4 combined these two policies to show their joint effect on the reduction of violence in Felonia. A method was mathematically modeled to successfully decrease the Felonian crime rate and violence.

## **Restatement of Problem**

Crime has been a prevalent problem in the city of Felonia. This paper seeks to investigate and mathematically model the supplied data to provide Felonia with a method to decrease violence.

## **Introduction**

For twenty-three days in October 2002, two men terrorized the citizens of Maryland, Virginia, and Washington D.C. Travelling along the Capital Beltway and Interstate 95, John Allen Muhammed and Lee Boyd Malvo murdered ten innocent people and critically injured three others (“A Byte Out of History: the Beltway Snipers, Part 1”). This heinous crime instilled terror in the citizens of Virginia, Maryland, and the Washington area. Schools and businesses were closed, and people were afraid to leave their homes until the serial killers were found and arrested. Crimes such as this that jeopardize the safety of innocent citizens have resulted in the efforts of government officials to reduce crime rates both nationally and locally.

Research has shown that one of the most effective ways to prevent crime, and thus lower crime rate, is minimizing the prevalence of minor crimes. Minor crimes include prostitution, public drunkenness, disruption of order, and excessive panhandling. When seemingly harmless crimes are strictly enforced by police, the general population realizes that unlawful actions, no matter how small, will not be tolerated. If law enforcement cracks down on small offenses, a drop in violent crimes will almost assuredly follow. This theory, often referred to as the “broken windows” policy and successfully utilized in New York, not only lessens the number of criminals in the population, but also helps maintain an atmosphere in which individuals are more unlikely to display criminal behavior (Kelling and Corbett 2-3). Another efficacious method of causing crime rates to decline is the “three strikes” philosophy. Currently in place in California,

this policy allows the judicial system to sentence criminals convicted of two violent felonies and a third felony to anywhere from twenty-five years behind bars to life in prison (Reynolds). These methods have been proven to influence crime rate more than other factors such as graduation rate, high school dropout rate, or incarceration rate.

The goals of this paper are threefold. First, a mathematical way to represent crime rate as a function of the supplied data will be developed. Second, the “broken windows” and “three strikes” philosophies of reducing crime rate will be taken into consideration and mathematically modeled. Third, an optimal plan for crime reduction will be created for the city of Felonia.

### **Assumptions**

To adequately analyze the situation presented by the scenario, several assumptions were developed. These included:

1. The city of Felonia is an average city in the United States with no current plan for crime reduction. This means that the city has not yet instituted a plan such as the “broken windows” or “three strikes” policies.
2. The unemployment rate of the city is equal to that of the county.
3. The high school enrollment rate, dropout rate, and graduation rate of the city are equal to those of the county.
4. The total population (the sum of the city population and the county population) includes the imprisoned population.
5. Plans to lower crime rate used in New York and California can be implemented in smaller cities, including Felonia
6. Property crimes are defined as petty crimes and misdemeanors. Violent crimes are defined as the incidence of violence as given in the supplied data.

7. The effectiveness of crime reduction policies implemented in New York and California (the “broken windows” and “three strikes” policies) will be similar to their original locations once implemented in Felonia.

### **Model 1**

The purpose of this model was to develop a numerical representation of the crime rate in Felonia from 2000 to 2008. The goal was not to determine what factors increase or decrease crime rate, but rather to create a new variable that could be used in future models. Multiple linear regression was performed on the given data using six explanatory variables: unemployment rate, graduation rate, high school dropout rate, parole violation rate, incarceration rate, and parole release rate. Unemployment rate ( $r_u$ ), graduation rate ( $r_g$ ), high school dropout rate ( $r_{hsd}$ ), and parole violation rate ( $r_{pv}$ ) were given. Incarceration rate ( $r_i$ ) was calculated by dividing the prison population by the total population, which was the sum of the city and county populations. Parole release rate ( $r_{pr}$ ) was calculated by dividing the number of individuals released on parole by the prison population. These variables were used to estimate crime rate ( $r_c$ ), which was calculated by dividing the incidence of violence by the total population. The raw data are listed in table 1.

Before multiple linear regression could be executed, the conditions for this statistical test had to be met. These conditions are as follows:

1. The mean response  $\mu_y$  is a linear function of the explanatory variables:

$$\mu_y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p$$

2. The residuals are independent and normally distributed with mean 0 and standard deviation  $\sigma$ . In other words, they are an SRS from the  $N(0, \sigma)$  distribution (Yates, Moore, and Starnes 9).

It was reasonable to assume for this model that crime rate reacts approximately linearly to the explanatory variables defined above. The residual plots shown in graphs 1 through 6 display no significant pattern. Therefore, it was reasonable to assume that the residuals are normally distributed and independent for each explanatory variable. Because both conditions were met, regression could proceed.

The multiple linear regression equation is shown in equation 1.  $t$ -tests for slope were conducted on each coefficient, and the results are shown in table 2. The hypotheses for these significance tests are explained below, where  $\beta$  is the population coefficient:

$$H_0: \beta_u = \beta_g = \beta_{hsd} = \beta_{pv} = \beta_i = \beta_{pr} = 0$$

$H_a$ : at least one of the above is not equal to 0

At a level of significance ( $\alpha$ ) of 0.05, the null hypothesis could not be rejected. All p-values were greater than  $\alpha$ ; this indicated that the probability of these results occurring, if it is assumed that the null hypothesis is true, was greater than 0.05. Therefore, it was concluded that no coefficient in the multiple linear regression equation was statistically different from 0. These results of the  $t$ -tests implied that there was no relationship between unemployment rate, graduation rate, high school dropout rate, parole violation rate, incarceration rate, or parole release rate and crime rate.

The multiple linear regression statistics are shown in tables 3 and 4. The multiple R of 0.9691 indicated that there was a strong positive correlation between  $r_c$  and the six explanatory variables ( $r_u$ ,  $r_g$ ,  $r_{hsd}$ ,  $r_{pv}$ ,  $r_i$ , and  $r_{pr}$ ). The  $R^2$  of 0.9391 described the percentage (93.91%) of

the change in  $r_c$  that was explained by changes in the explanatory variables. However, due to the number of independent variables present in this model, the adjusted  $R^2$  value provided a more accurate representation of this percentage (Clyde). Therefore, this model suggested that 75.64% of the change in  $r_c$  could be explained by changes in the explanatory variables. The  $F$ -statistic was 5.1405, and the degrees of freedom were 6 (regression) and 2 (residual). This  $F$ -distribution, along with the two-sided alternative hypothesis given above, resulted in a p-value of 0.1718. The standard error of the regression model—the square root of the mean square error, or the mean of squares of the residuals in table 4—was low ( $4.753 \times 10^{-5}$ ), indicating that the model predicted crime rate accurately. Because the correlation was high, the adjusted  $R^2$  was respectable, and the standard error was low, this model reasonably estimated  $r_c$  as a function of  $r_u$ ,  $r_g$ ,  $r_{hsd}$ ,  $r_{pv}$ ,  $r_i$ , and  $r_{pr}$ . However, because the p-value was greater than  $\alpha = 0.05$ , the null hypothesis cannot be rejected. This model again implied that there was no relationship between unemployment rate, graduation rate, high school dropout rate, parole violation rate, incarceration rate, or parole release rate and crime rate.

While equation 1 achieved model 1's goal of mathematically representing crime rate as a function of several other rates, this model can be improved. The hypothesis that there is a relationship between the explanatory variables and crime rate was not supported by the results of model 1. Because the final goal is to develop a plan for reducing crime rate, a successful model must reflect the variables that contribute to crime rate the most. According to crime research, the "broken windows" policy is an effective method of reducing crime rate (Kelling and Ronald 2). This philosophy was implemented in model 2.

## **Model 2**

The purpose of model 2 was to mathematically model how implementing the “broken windows” policy would affect  $r_c$  and the multiple linear regression equation from model 1. This model took information from New York’s execution of the plan and applied it to the supplied data. This caused the calculation of  $r_c$  to change for this model. Data from New York from the years 1994 to 2002 was used to calculate a new incidence of crime for Felonia for the years 2000 to 2008; these nine years were chosen because New York initiated the “broken windows” plan in 1994 (“New York Crime Rates 1960-2009”). The yearly difference in the number of violent crimes in New York was divided by the preceding year to yield the change in violent crime rate. This was then multiplied by the incidence of violence in 2000 in Felonia to give the new incidence of violence, which was then divided by the incidence of violence in 2000 to yield  $r_c$ . The raw data for the calculation of  $r_c$  are shown in table 5.

In addition to the six explanatory variables from model 1, this model also took into consideration property crime rate ( $r_p$ ). This was calculated by first determining the number of property crimes, which was found by dividing the number of violent crimes by the proportion of violent crimes in relation to the total number of crimes. The number of property crimes was then divided by the total population to yield  $r_p$ . The calculation of  $r_p$  for the years 2000 to 2008 in Felonia are given in table 6.

The raw data used for multiple linear regression are given in table 7. The conditions for conducting the regression were met as stated in model 1 (see graphs 6 through 13). The multiple linear regression equation is shown in equation 2.  $t$ -tests for slope were conducted on each coefficient, and the results are shown in table 8. The hypotheses are explained below:

$$H_0: \beta_u = \beta_g = \beta_{hsd} = \beta_{pv} = \beta_i = \beta_{pr} = \beta_p = 0$$

$H_a$ : at least one of the above is not equal to 0

At a level of significance ( $\alpha$ ) of 0.05, the null hypothesis cannot be rejected. Every p-value had a value greater than  $\alpha$ , indicating that the probability of these results occurring, assuming the null hypothesis is true, is greater than 0.05. Consequently, it was concluded that no coefficient in the multiple linear regression equation is significantly different from 0. The results of these  $t$ -tests implied that there was not a relationship between unemployment rate, graduation rate, high school dropout rate, parole violation rate, incarceration rate, parole release rate, or property crime rate and violent crime rate.

The multiple linear regression statistics are shown in tables 9 and 10. The multiple R of 0.9971 indicated a strong positive correlation between  $r_c$  and the seven explanatory variables ( $r_u$ ,  $r_g$ ,  $r_{hsd}$ ,  $r_{pv}$ ,  $r_i$ ,  $r_{pr}$ , and  $r_p$ ). The  $R^2$  of 0.9941 described the percentage (99.41%) of the change in  $r_c$  that is explained by changes in the explanatory variables. However, due to the number independent variables present in the model, the adjusted  $R^2$  value proved to be a more accurate representation of this percentage (Clyde). Therefore, this model suggested that 95.31% of the change in  $r_c$  could be explained by changes in the explanatory variables. The standard error of the regression model was low ( $4.15 \times 10^{-5}$ ), signifying that it predicts violent crime rate accurately. Because the correlation is high, the adjusted  $R^2$  is high, and the standard error is low, this model estimates  $r_c$  as a function of  $r_u$ ,  $r_g$ ,  $r_{hsd}$ ,  $r_{pv}$ ,  $r_i$ ,  $r_{pr}$ , and  $r_p$  very well.

### **Model 3**

The purpose of model 3 was to model how instituting the “three strikes” plan would affect  $r_c$  and the multiple linear regression equation from model 1. This model used information from California’s employment of the policy and applied it to the given data. The methodology



for recalculating  $r_c$  was the same as in model 2, but California data from 1994 to 2002 was used in place of the New York data (Reynolds). The raw data for this calculation is shown in table 11. In addition,  $r_i$  was recalculated to account for the change in prison population as a result of the expected increased number of incarcerated criminals due to the enforcement of the “three strikes” rule. This calculation was similar to the calculation of  $r_p$  in model 2 and is shown in table 12. The raw data used for regression are given in table 13.

The conditions for conducting multiple linear regression were met as stated in model 1 (see graphs 14 through 19). The multiple linear regression equation is shown in equation 3.  $t$ -tests for slope were conducted on each coefficient, and the results are shown in table 14. The hypotheses are explained below:

$$H_0: \beta_u = \beta_g = \beta_{hsd} = \beta_{pv} = \beta_i = \beta_{pr} = 0$$

$$H_a: \text{at least one of the above is not equal to 0}$$

At  $\alpha = 0.05$ , the null hypothesis could not be rejected. All p-values were much greater than  $\alpha$ , so it was concluded that no coefficient in the multiple linear regression equation was statistically different from 0. These  $t$ -tests implied that there was no relationship between unemployment rate, graduation rate, high school dropout rate, parole violation rate, incarceration rate, or parole release rate and crime rate.

The multiple linear regressions statistics are shown in tables 15 and 16. The multiple R of 0.9847 indicated that there was a strong positive correlation between  $r_c$  and the six explanatory variables. The  $R^2$  of 0.9696 described the percentage (96.96%) of the change in  $r_c$  that was explained by changes in the explanatory variables. However, the more appropriate adjusted  $R^2$  suggested that 87.82% of the change in  $r_c$  could be explained by changes in the explanatory

variables. The standard error of the regression model was low ( $6.668 \times 10^{-5}$ ), indicating that it predicted violent crime rate accurately. Because the correlation was high, the adjusted  $R^2$  was respectable, and the standard error was low, this model was a reasonable estimate of  $r_c$  as a factor of the explanatory variables.

#### **Model 4**

The purpose of model 4 was to combine models 2 and 3 in order to represent the effect of implementing both the “broken windows” and “three strikes” philosophies in Felonia. The goal of this model was to determine how employing both plans would affect  $r_c$  and the multiple linear regression equation from model 1. Table 19 shows the calculations for property rate for the California-based data. The conditions for multiple linear regression were met as stated earlier (see graphs 20 to 26), and the hypotheses were the same as in model 2. The equation is given in equation 4. Tables 17 and 18 show the results of the regression. Note that this model, which combines both the “broken windows” and “three strikes” policy, was the only one that was statistically significant. Therefore, it was the best representation for the data and crime reduction.

#### **Further Improvements**

While a model was established that could successfully decrease the crime rate and violence in Felonia, there are multiple improvements that could be implemented to advance future studies. The crime rate was found to lessen from 2000 to 2008, but whether this is a continuing trend is unknown. With additional data from numerous years in the past, extrapolation of the rate of crime and violence reduction would be valid to determine if the methods used in these models are plausible for decreasing crime in the long run.

A list of factors to consider when modeling a solution and data were given to use while developing the solution to Felonia’s problem. Other factors and issues that could have an effect

on violence, such as differences in socioeconomic status and abortion, could be considered. This would enable the model to be even more applicable to the world and its events today.

Furthermore, obtaining data from other cities and regions that have reduced their crime problems, as New York and California have, would allow for the employment of other policies and comparison of the various methods to determine the extent of success of these different strategies. This would provide more options than the “broken windows” policy and the “three strikes” law for solving the violence problem in Felonia.

### **Conclusion**

The purpose of this mathematical model was to establish a plan for the city of Felonia to reduce violence using a set of data available for the following: incidents of violence, homicides, assaults, regional population, unemployment, unemployment rate, high school enrollment, high school dropouts, graduation rate, dropout rate, prison population, released on parole, parole violations, percent of parole violations, and juvenile inmates.

The first model used multiple linear regression to develop a numerical representation of the crime rate in Felonia from 2000 to 2008. Models 2 and 3 used the implementation of the “broken windows” policy and the “three strikes” law and additional variables, property crime rate and prison population rate, respectively to display their potential effect on violent crime rate. Model 4 combined the use of both policies to show the reduction of violent crime rate in Felonia. It was the most successful model in representing the data for crime rate reduction in Felonia.

Although the cause of crime cannot explicitly be determined, the factors that have an effect on crime rate can be displayed through statistical analysis. By changing these factors, the crime rate of a city, such as Felonia, can be reduced.

**Contact: John Doe**  
ATAA Corporations  
Phone: (555) 867-5309  
Fax: (555) 867-5309

12345 Main Street  
Felonia, USA 12345  
www.ATAA.com

**ATAA CORPORATIONS**

---

# PRESS RELEASE

**ATAA Corporations Announces Felonia Crime Problem Solution**

*New York and Los Angeles crime reduction attempts used as models.*

**Felonia, November 11, 2010:** ATAA Corporations has announced a possible solution for the excessive violent crime rate in Felonia. This small city has had an average of 725 incidents of violence every year since 2000, putting the safety of its citizens at great risk.

ATAA Corporations analyzed Felonian crime data between the years 2000 and 2008, realizing that there was little correlation between crime rate and the variables previously believed to be at the root of its crime problems: unemployment rate, graduation rate, high school dropout rate, parole violation rate, incarceration rate, and parole release rate. In a desperate attempt to solve the problem, the company studied historical crime reduction efforts in two other US regions, New York and California.

In 1994, New York implemented the “Broken Window” policy, a proactive solution aimed at cracking down on petty crimes. ATAA Corporations examined crime data from New York, displaying obvious correlation between non-violent and violent crimes, suggesting that the “Broken Window” policy was successful in reducing violent crime from 195,352 cases in 1993 to 75,176 in 2009, a reduction of over 60%.

California also implemented a crime reduction policy in 1994, the “Three Strikes Law,” which sentenced any violator of three felonies, at least two being violent, to at least 25 years in prison. Criminal data from Los Angeles revealed that after the implementation of this law, prison population increased approximately 36% from 1993. After analysis of the data, ATAA Corporations concluded that an increase in prison populations inversely correlates to crime rate,

since there is an obvious drop of crime from 336,100 cases in 1993 to 191,493 in 2007, a decrease of 43%.

Concluding that these two methods are effective at reducing crime rate, ATAA Corporations implemented these variables into the Felonian crime data and created a model using multiple linear regression that may be used to determine the effectiveness of the changes.

ATAA Corporations suggests the implementations of the “Broken Window” Policy and the “Three Strikes Law” to effectively reduce the Felonian crime rate.

Headquartered in Felonia, USA, ATAA Corporations is one of the nation's leading statistical analysis agencies.

## **Bibliography**

“A Byte Out of History: the Beltway Snipers, Part 1.” *The Federal Bureau of Investigation*. 22

October 2007. Web. 10 November 2010.

Clyde, Merlise. "Interpretation in Multiple Regression." *STA 242/ENV 255: Applied Regression*

*Analysis*. Department of Statistical Science, Duke University. Web. 9 Nov. 2010.

Kelling, George L. and Ronald Corbett. “This Works: Preventing and Reducing Crime.” *Civic*

*Bulletin*. 32. (2003): 1-9. *Manhattan Institute for Policy Research*. Web. 09 November

2010.

"New York Crime Rates 1960-2009." *The Disaster Center - Home Page*. 1997. Web. 10 Nov.

2010.

Reynolds, Mike. “15 Years of Three Strikes and Still Working!” *Three Strikes*. 2008. Web. 09

November 2010.

Yates, Daniel S., David S. Moore, and Daren S. Starnes. “Chapter 16: Multiple Linear

Regression.” *The Practice of Statistics: TI-83/89 Graphing Calculator Enhanced*. New

York: W.H. Freeman, 2003. CD-ROM.

**Appendix**

Equation 1. Model 1: Multiple Linear Regression Equation

$$r_c = 0.0016 + (8.895 \times 10^{-5})r_u - 0.0104r_g - 0.0246r_{hsd} + 0.0040r_{pv} + 0.0300r_i - 0.0037r_{pr}$$

Equation 2. Model 2: Multiple Linear Regression Equation

$$r_c = -0.0021 - (9.266 \times 10^{-6})r_u - 0.0014r_g - 0.0071r_{hsd} + 0.0015r_{pv} + 0.0124r_i - 0.0016r_{pr} + 0.2774r_p$$

Equation 3. Model 3: Multiple Linear Regression Equation

$$r_c = 0.0034 - (2.046 \times 10^{-6})r_u - 0.0009r_g - 0.0009r_{hsd} + 0.0010r_{pv} - 0.0049r_i - 0.0007r_{pr}$$

Equation 4. Model 4: Multiple Linear Regression Equation

$$r_c = 0.0006 - (1.706 \times 10^{-5})r_u - 0.0015r_g - 0.0028r_{hsd} + 0.0013r_{pv} + 0.0019r_i - 0.0008r_{pr} + 0.6241r_p$$

Table 1. Model 1: Raw Data

Year	$r_c$	$r_u$	$r_g$	$r_{hsd}$	$r_{pv}$	$r_i$	$r_{pr}$
2000	0.001360	10.5	0.840	0.02460	0.7086	0.2786	0.8189
2001	0.001476	11.1	0.836	0.02588	0.7062	0.2785	0.8200
2002	0.001274	12.7	0.877	0.02302	0.7295	0.2711	0.7739
2003	0.001316	12.7	0.900	0.00811	0.6762	0.2719	0.7506
2004	0.001218	11.8	0.891	0.01332	0.6501	0.2767	0.7474
2005	0.001142	10.5	0.898	0.00895	0.6596	0.2781	0.7727
2006	0.001210	9.9	0.920	0.01306	0.6845	0.2920	0.7885
2007	0.001265	10.3	0.884	0.01898	0.6732	0.2902	0.8275
2008	0.001270	11.8	0.890	0.01537	0.6732	0.2870	0.8275

Table 2. Model 1: *t*-tests for Slope on Multiple Linear Regression Coefficients

	Coefficient	Standard Error	<i>t</i> -statistic	p-value
Intercept	0.0016	0.0014	1.1470	0.3701
City Unemployment Rate	$8.895 \times 10^{-5}$	$3.306 \times 10^{-5}$	2.6907	0.1148
Graduation Rate	-0.0104	0.0031	-3.3144	0.0802
High School Dropout Rate	-0.0246	0.0107	-2.2897	0.1492
Parole Violation Rate	0.0040	0.0017	2.4002	0.1384
Incarceration Rate	0.0300	0.0114	2.6217	0.1199
Parole Release Rate	-0.0037	0.0019	-1.9593	0.1892

Table 3. Model 1: Multiple Linear Regression Statistics

Multiple R	0.9691
R <sup>2</sup>	0.9391
Adjusted R <sup>2</sup>	0.7564
Standard Error	$4.753 \times 10^{-5}$

Observations	9
--------------	---

Table 4. Model 1: Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean of Squares	F-statistic	p-value
Regression	6	$6.968 \times 10^{-8}$	$1.161 \times 10^{-8}$	5.1405	0.1718
Residual	2	$4.518 \times 10^{-9}$	$2.259 \times 10^{-9}$		
Total	8	$7.420 \times 10^{-8}$			

Table 5. Model 2: Calculation of  $r_c$

NY Year	NY Violent Crime	NY Violent Crime Change	Felonia Year	Felonia Violent Crime	$r_c$
1993	195352				
1994	175433	-0.1020	2000	675.3226	0.001222
1995	152683	-0.1297	2001	654.4813	0.001065
1996	132206	-0.1341	2002	651.1459	0.000910
1997	124890	-0.0553	2003	710.3859	0.000850
1998	115915	-0.0719	2004	697.9588	0.000782
1999	107147	-0.0756	2005	695.1175	0.000722
2000	124890	0.1656	2006	876.5274	0.000843
2001	98022	-0.2151	2007	590.2197	0.000659
2002	95030	-0.0305	2008	729.0461	0.000631

Table 6. Model 2: Calculation of  $r_p$

NY Year	NY Violent Crime	NY Property Crime	NY Rate Violent to Property	Felonia Year	Felonia Violent Crime	Felonia Property Crime	Total Population	$r_p$
1994	175,433	745,845	0.2352	2000	675.3226	2871.1016	552822	0.0052
1995	152,683	674,342	0.2264	2001	587.7473	2595.8536	551649	0.0047
1996	132,206	619,250	0.2135	2002	508.9219	2383.7790	559065	0.0043
1997	124,890	584,438	0.2137	2003	480.7592	2249.7716	565536	0.0040
1998	115,915	536,287	0.2161	2004	446.2103	2064.4162	570708	0.0036
1999	107,147	489,596	0.2188	2005	412.4582	1884.6809	571049	0.0033
2000	124,890	483,078	0.2585	2006	480.7592	1859.5902	570287	0.0033
2001	98,022	458,003	0.2140	2007	377.3319	1763.0649	572970	0.0031
2002	95,030	442,091	0.2150	2008	365.8143	1701.8123	579447	0.0029

Table 7. Model 2: Raw Data for Multiple Linear Regression

Year	$r_c$	$r_u$	$r_g$	$r_{hsd}$	$r_{pv}$	$r_i$	$r_{pr}$	$r_p$
2000	0.0012	10.5	0.840	0.0246	0.7086	0.2786	0.8189	0.0052
2001	0.0011	11.1	0.836	0.0259	0.7062	0.2785	0.8200	0.0047
2002	0.0009	12.7	0.877	0.0230	0.7295	0.2711	0.7739	0.0043
2003	0.0009	12.7	0.900	0.0081	0.6762	0.2719	0.7506	0.0040



2004	0.0008	11.8	0.891	0.0133	0.6501	0.2767	0.7474	0.0036
2005	0.0007	10.5	0.898	0.0090	0.6596	0.2781	0.7727	0.0033
2006	0.0008	9.9	0.920	0.0131	0.6845	0.2920	0.7885	0.0033
2007	0.0007	10.3	0.884	0.0190	0.6732	0.2902	0.8275	0.0031
2008	0.0006	11.8	0.890	0.0154	0.6732	0.2870	0.8275	0.0029

Table 8. Model 2: *t*-tests for Slope on Multiple Linear Regression Coefficients

	Coefficients	Standard Error	<i>t</i> -statistic	p-value
Intercept	-0.0021	0.0035	-0.5948	0.6584
City Unemployment Rate	-9.266 x 10 <sup>-6</sup>	2.938 x 10 <sup>-5</sup>	-0.3154	0.8055
Graduation Rate	-0.0014	0.0070	-0.1942	0.8779
High School Dropout Rate	-0.0071	0.0167	-0.4254	0.7439
Parole Violation Rate	0.0015	0.0036	0.4268	0.7432
Incarceration Rate	0.0124	0.0149	0.8321	0.5582
Parole Release Rate	-0.0016	0.0035	-0.4459	0.7330
Property Crime Rate	0.2774	0.1160	2.3913	0.2522

Table 9. Model 2: Multiple Linear Regression Statistics

Multiple R	0.9971
R <sup>2</sup>	0.9941
Adjusted R <sup>2</sup>	0.9531
Standard Error	4.150 x 10 <sup>-5</sup>
Observations	9

Table 10. Model 2: Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean of Squares	<i>F</i> -statistic	p-value
Regression	7	2.918 x 10 <sup>-7</sup>	4.168 x 10 <sup>-8</sup>	24.2053	0.1553
Residual	1	1.722 x 10 <sup>-9</sup>	1.722 x 10 <sup>-9</sup>		
Total	8	2.935 x 10 <sup>-7</sup>			

Table 11. Model 3: Calculation of *r<sub>c</sub>*

CA Year	CA Violent Crime	CA Violent Crime Change	Felonia Year	Felonia Violent Crime	Total Population	<i>r<sub>c</sub></i>
1993	336100					
1994	318946	-0.0510	2000	713.6191	552822	0.0013
1995	304998	-0.0925	2001	682.4115	551649	0.0012
1996	274675	-0.1828	2002	614.5659	559065	0.0011
1997	257409	-0.2341	2003	575.9344	565536	0.0010
1998	229786	-0.3163	2004	514.1299	570708	0.0009
1999	207874	-0.3815	2005	465.1034	571049	0.0008
2000	210492	-0.3737	2006	470.961	570287	0.0008

2001	210510	-0.3737	2007	471.0012	572970	0.0008
2002	207988	-0.3812	2008	465.3585	579447	0.0008

Table 12. Model 3: Calculation of  $r_p$

CA Year	CA Prison Population	CA Change in Prison Population	Felonia Year	Felonia Prison Population	Felonia Prison Population	Total Population	$r_p$
1993	119951						
1994	125605	0.0471	2000	154014	161273.5906	552822	0.2917
1995	135133	0.1266	2001	153649	173507.2977	551649	0.3145
1996	145565	0.2135	2002	151579	186901.7175	559065	0.3343
1997	155276	0.2945	2003	153783	199370.3918	565536	0.3525
1998	159563	0.3302	2004	157895	204874.7896	570708	0.3590
1999	160681	0.3396	2005	158837	206310.2728	571049	0.3613
2000	160655	0.3393	2006	166547	206276.8895	570287	0.3617
2001	157142	0.3101	2007	166277	201766.2878	572970	0.3521
2002	159695	0.3313	2008	166277	205044.2742	579447	0.3539

Table 13. Model 3: Raw Data for Multiple Linear Regression

Year	Violent Crime rate with three strikes	City Unemployment Rate	Graduation Rate	HS Dropout Rate	Parole Violation Rate	Incarceration Rate with three strikes	Parole Release Rate
2000	0.0013	10.5	0.840	0.0246	0.7086	0.2917	0.8189
2001	0.0012	11.1	0.836	0.0259	0.7062	0.3139	0.8200
2002	0.0011	12.7	0.877	0.0230	0.7295	0.3300	0.7739
2003	0.0010	12.7	0.900	0.0081	0.6762	0.3521	0.7506
2004	0.0009	11.8	0.891	0.0133	0.6501	0.3658	0.7474
2005	0.0008	10.5	0.898	0.0090	0.6596	0.3697	0.7727
2006	0.0008	9.9	0.920	0.0131	0.6845	0.3837	0.7885
2007	0.0008	10.3	0.884	0.0190	0.6732	0.3735	0.8275
2008	0.0008	11.8	0.890	0.0154	0.6732	0.3750	0.8275

Table 14. Model 3:  $t$ -tests for Slope on Multiple Linear Regression Coefficients

	Coefficients	Standard Error	$t$ -statistic	p-value
Intercept	0.0034	0.0031	1.1275	0.3766
Unemployment Rate	$-2.046 \times 10^{-6}$	$3.18 \times 10^{-5}$	-0.0644	0.9545
Graduation Rate	-0.0009	0.0054	-0.1684	0.8817
High School Dropout Rate	-0.0009	0.0140	-0.0673	0.9525
Parole Violation Rate	0.0010	0.0033	0.3053	0.7890
Incarceration Rate	-0.0049	0.0040	-1.2290	0.3441
Parole Release Rate	-0.0007	0.0015	-0.4719	0.6835

Table 15. Model 3: Multiple Linear Regression Statistics

Multiple R	0.9847
R <sup>2</sup>	0.9696
Adjusted R <sup>2</sup>	0.8782
Standard Error	6.668 x 10 <sup>-5</sup>
Observations	9

Table 16. Model 3: Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean of Squares	F-statistic	p-value
Regression	6	2.832 x 10 <sup>-7</sup>	4.720 x 10 <sup>-8</sup>	10.6159	0.0886
Residual	2	8.892 x 10 <sup>-9</sup>	4.446 x 10 <sup>-9</sup>		
Total	8	2.921 x 10 <sup>-7</sup>			

Table 17. Model 4: Regression Statistics

Multiple R	0.999992369
R Square	0.999984738
Adjusted R Square	0.999877904
Standard Error	2.92799E-06
Observations	9

Table 18. Model 4: Analysis of Variance

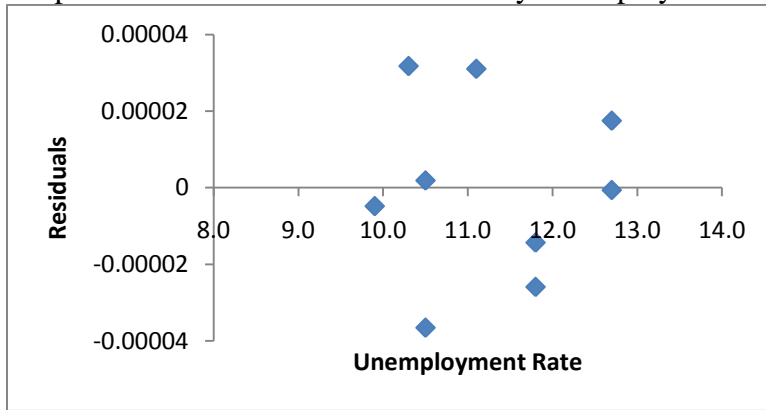
	Degrees of Freedom	Sum of Squares	Mean of Squares	F-statistic	p-value
Regression	7	5.62E-07	8.02E-08	9360.152	0.007958
Residual	1	8.57E-12	8.57E-12		
Total	8	5.62E-07			

Table 19. Model 4: Calculation of Property Rate for California Data

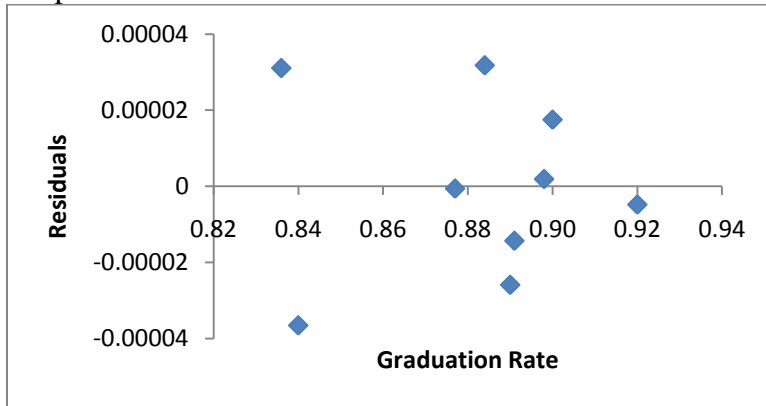
Year	Violent Crime	Property Crime	Proportion Violent to Property	Year	Violent Crime (With Three Strikes)	Property Crime (Violent Crime/Rate Violent to Property)	Total Population	Property Crime rate
1994	318946	692717	0.460427563	2000	713.6191372	1549.905338	552822	0.0028036
1995	304998	634134	0.480967745	2001	682.4114728	1418.830015	551649	0.002572
1996	274675	553974	0.495826519	2002	614.565903	1239.477679	559065	0.0022171
1997	257409	527422	0.488051314	2003	575.9344481	1180.069456	565536	0.0020866
1998	229786	464249	0.494962832	2004	514.1299375	1038.724332	570708	0.0018201

1999	207874	392293	0.529894747	2005	465.10338 59	877.727866 7	571049	0.0015 37
2000	210492	403296	0.521929303	2006	470.96097 59	902.346301 7	570287	0.0015 823
2001	210510	430996	0.488426807	2007	471.00124 96	964.323094 3	572970	0.0016 83
2002	207988	459225	0.452910882	2008	465.35845 28	1027.48348 7	579447	0.0017 732

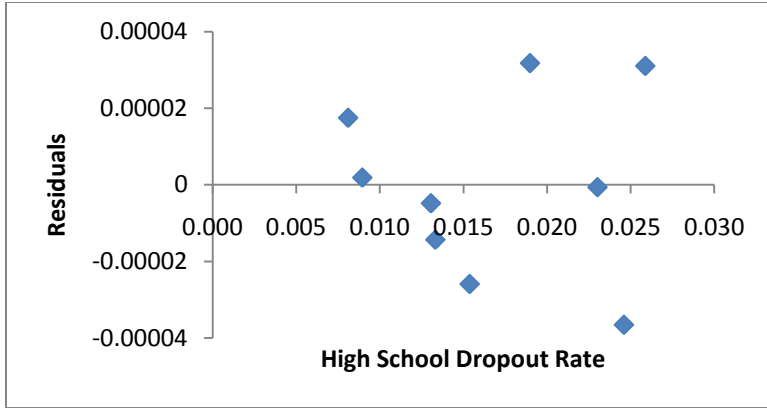
Graph 1. Model 1: Residual Plot for City Unemployment Rate



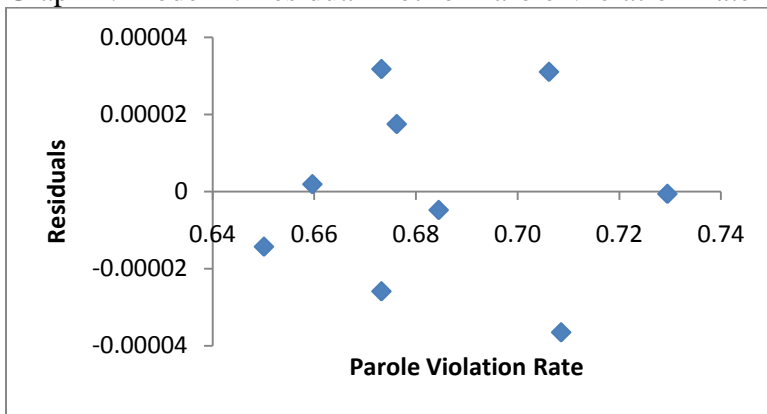
Graph 2. Model 1: Residual Plot for Graduation Rate



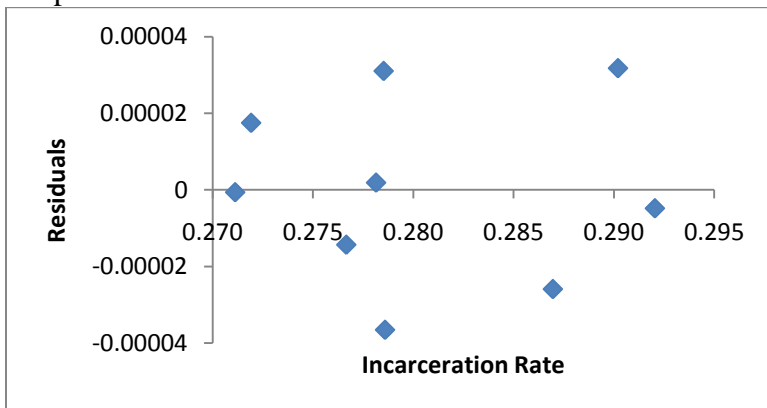
Graph 3. Model 1: Residual Plot for High School Dropout Rate



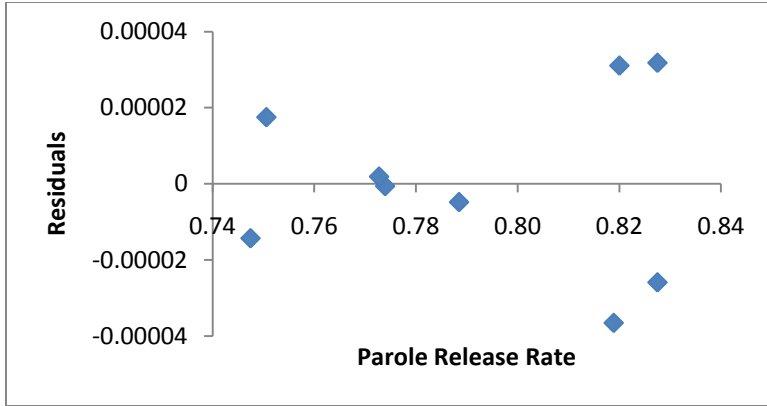
Graph 4. Model 1: Residual Plot for Parole Violation Rate



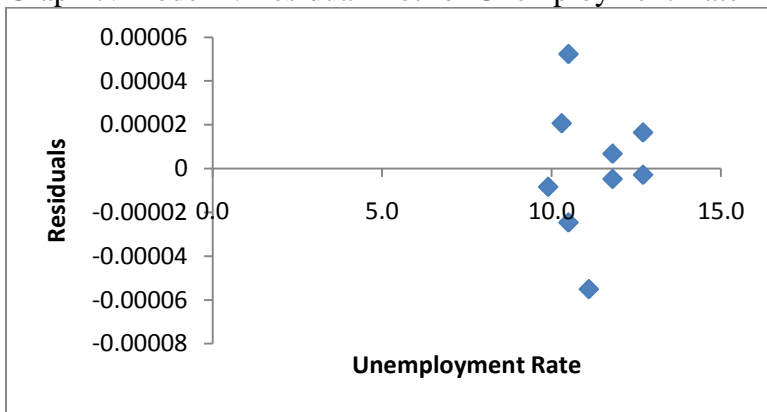
Graph 5. Model 1: Residual Plot for Incarceration Rate



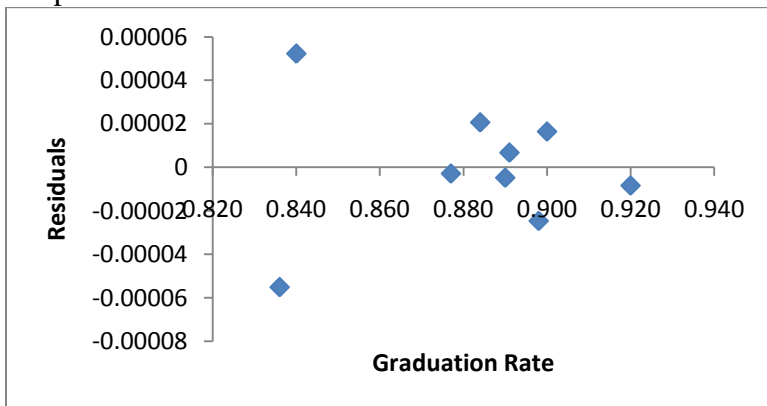
Graph 6. Model 1: Residual Plot for Parole Release Rate



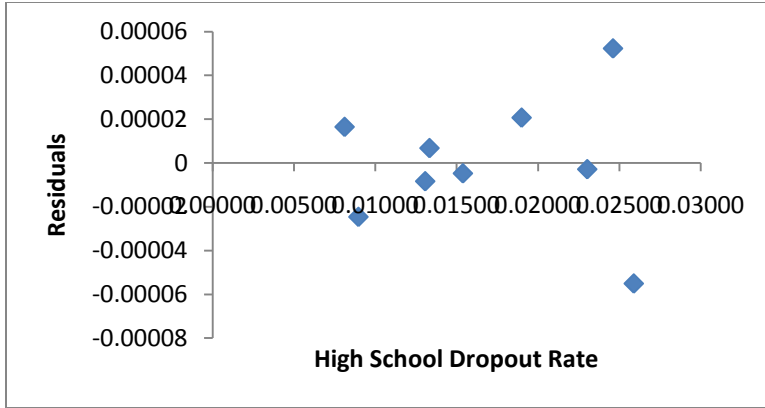
Graph 7. Model 2: Residual Plot for Unemployment Rate



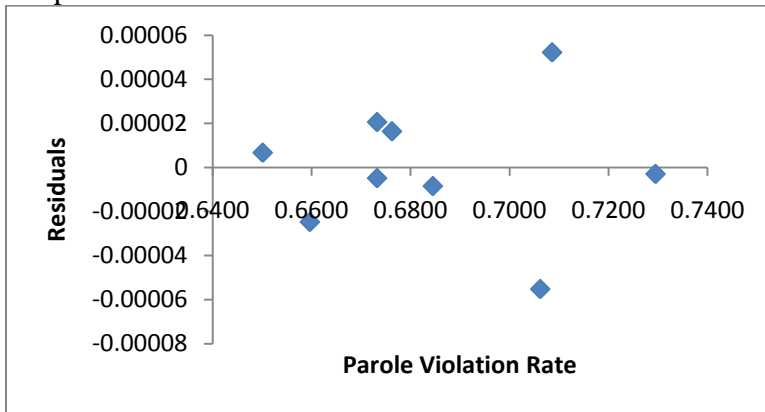
Graph 8. Model 2: Residual Plot for Graduation Rate



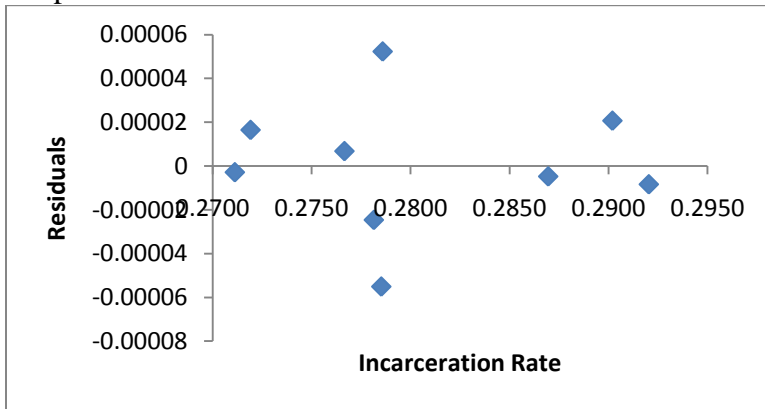
Graph 9. Residual Plot for High School Dropout Rate



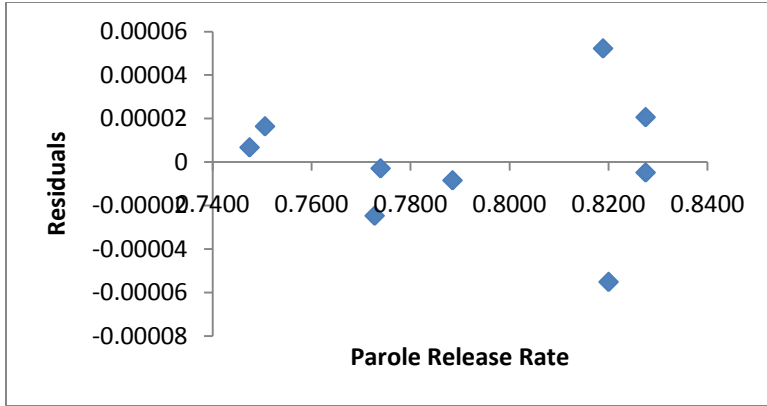
Graph 10. Model 2: Residual Plot for Parole Violation Rate



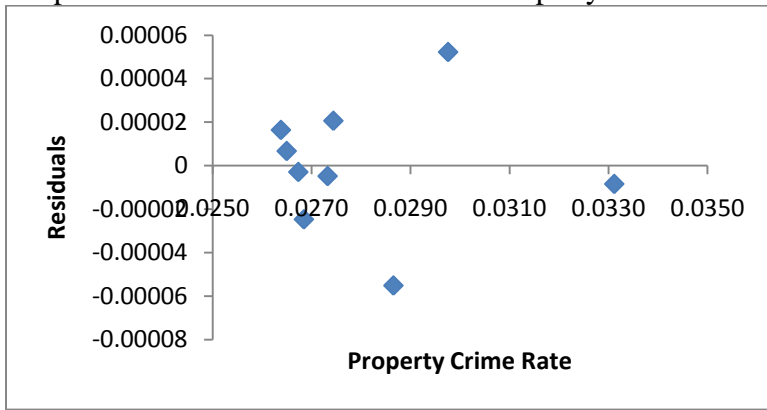
Graph 11. Model 2: Residual Plot for Incarceration Rate



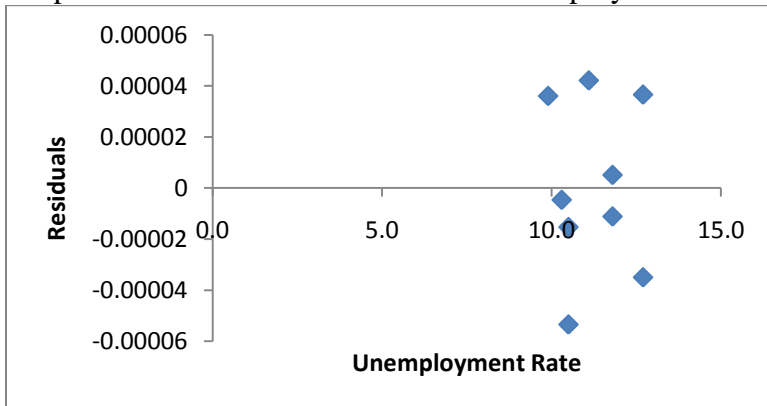
Graph 12. Model 2: Residual Plot for Parole Release Rate



Graph 13. Model 2: Residual Plot for Property Crime Rate

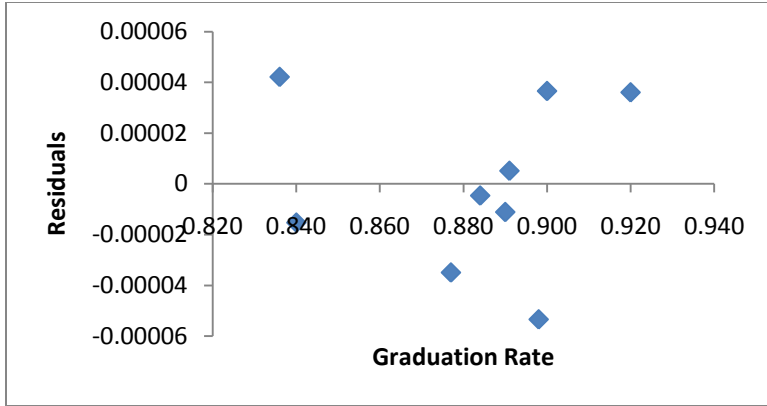


Graph 14. Model 3: Residual Plot for Unemployment Rate

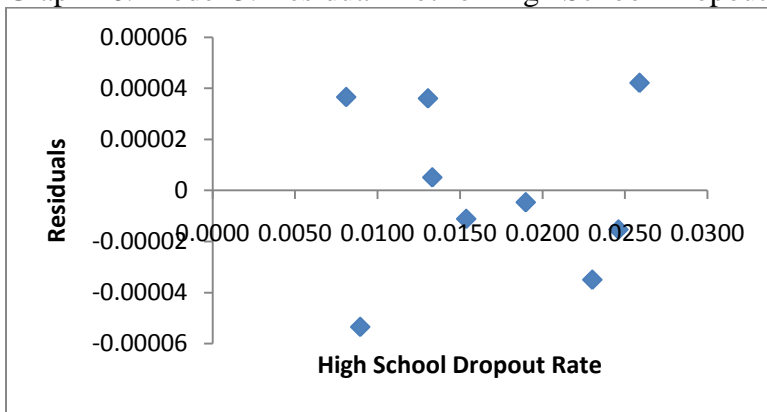


Graph 15. Model 3: Residual Plot for Graduation Rate

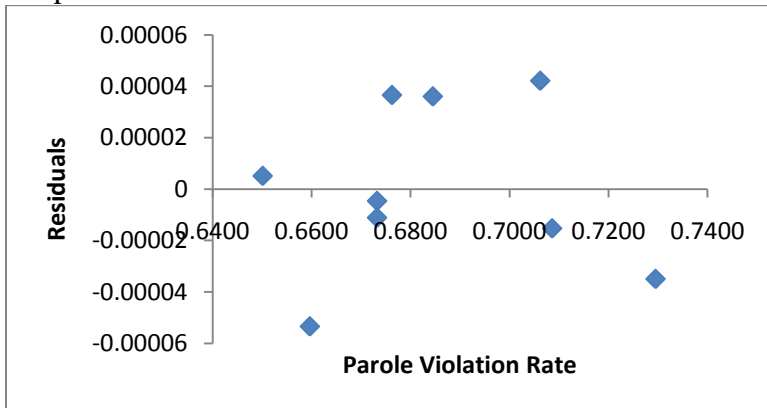




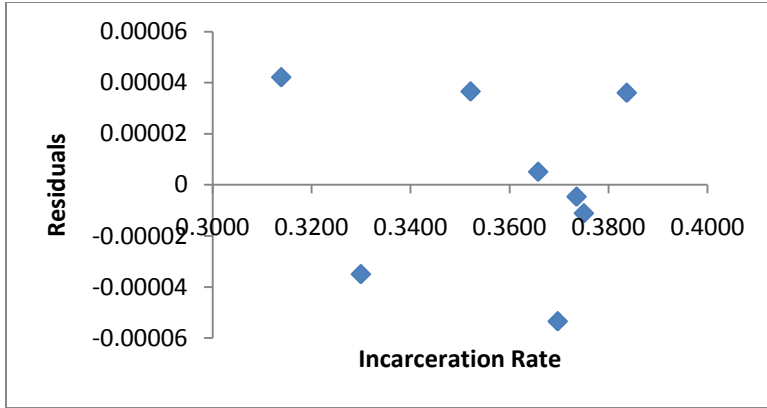
Graph 16. Model 3: Residual Plot for High School Dropout Rate



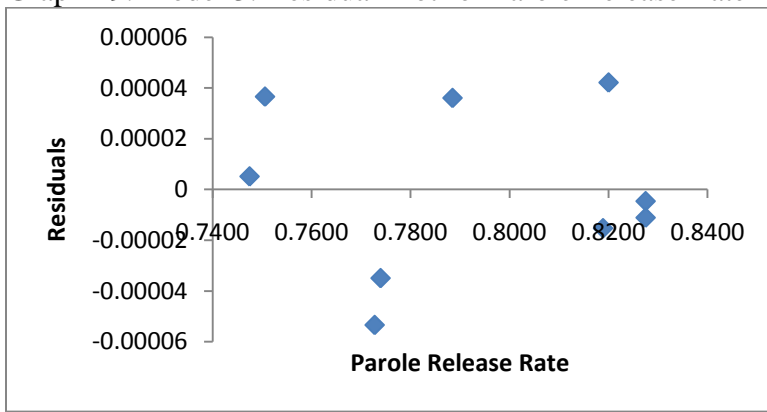
Graph 17. Model 3: Residual Plot for Parole Violation Rate



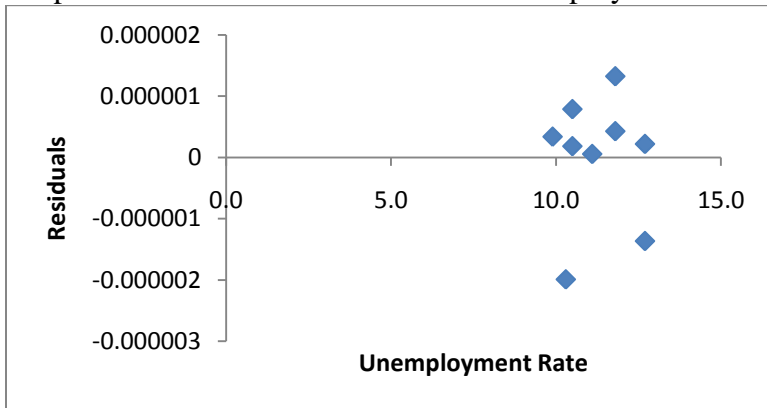
Graph 18. Model 3: Residual Plot for Incarceration Rate



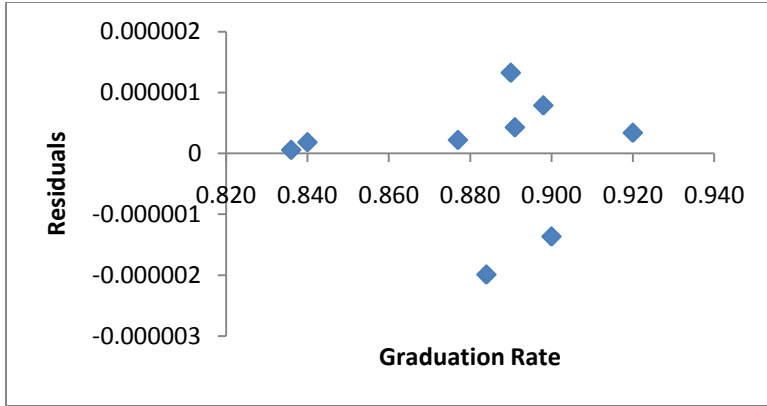
Graph 19. Model 3: Residual Plot for Parole Release Rate



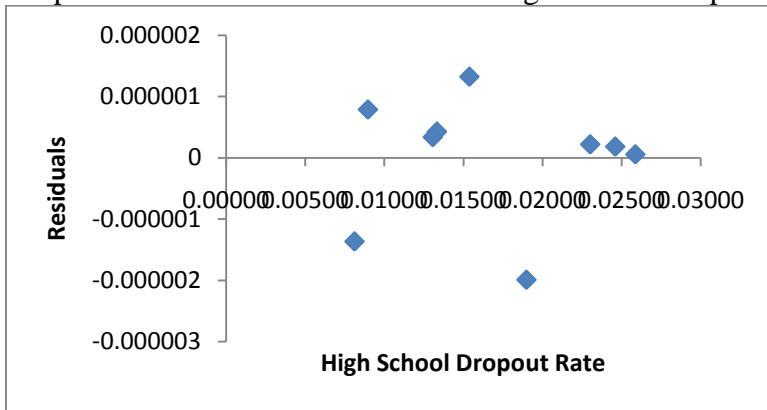
Graph 20. Model 4: Residual Plot for Unemployment Rate



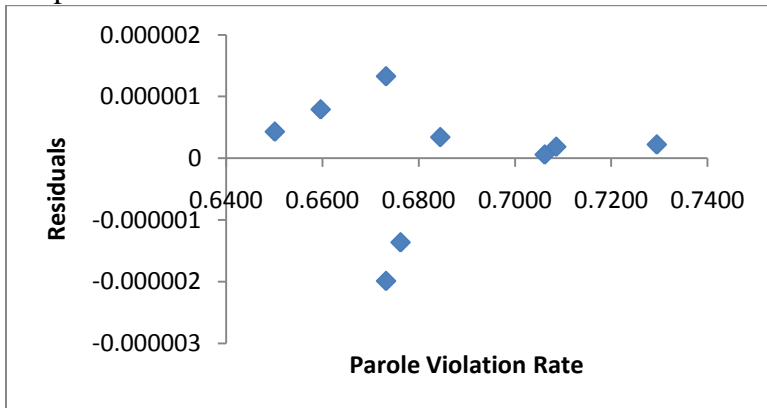
Graph 21. Model 4: Residual Plot for Graduation Rate



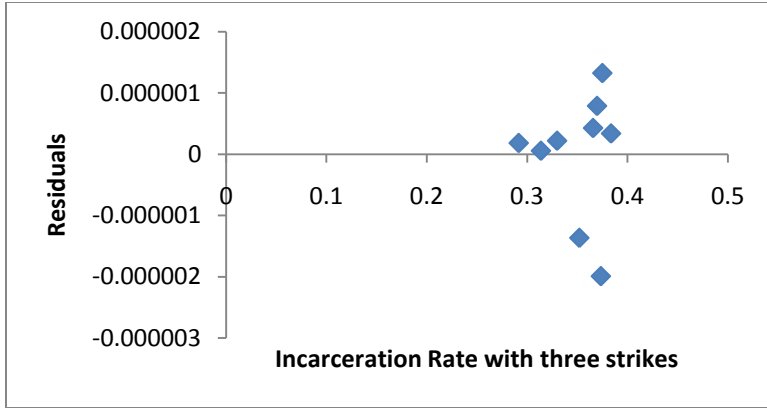
Graph 22. Model 4: Residual Plot for High School Dropout Rate



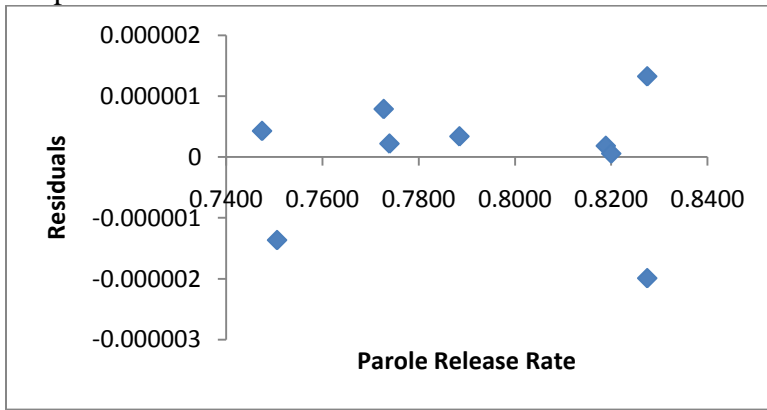
Graph 23. Model 4: Residual Plot for Parole Violation Rate



Graph 24. Model 4: Residual Plot for Incarceration Rate



Graph 25. Model 4: Residual Plot for Parole Release Rate



Graph 26. Model 4: Residual Plot for Property Crime Rate

