# America's Warzone: Modeling Armed Robberies in Chicago

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## 1   Introduction

The City of Chicago is frequently listed as one of the most dangerous and crime-ridden cities in the US. President Donald Trump frequently discusses the high-rate of crime in Chicago. According to the Chicago Tribune, there were 4,367 shooting victims in Chicago in 2016. In the same year there were also 785 homicides.[12] However, other reports conclude that Chicago should not be called the "crime capital" of America, as Chicago's violence rate is lower than cities like St. Louis and Detroit. [11] The goal of this project was to examine crime in Chicago, specifically armed robberies, from 2012-2016.

## 2   Data

The crime data used for this project came from the City of Chicago's website. [6]The data contained every reported crime in Chicago from 2001 to the present (Table 1). In addition to the type of crime reported (battery, assault, etc.), there was information on the location and time of the crime. The data set was reduced to only consider armed robberies, which we define to be robberies committed with a gun or another type of firearm.

| Case Number | Date | Block | Description | Beat | District | Ward | Community Area | Location |
|---|---|---|---|---|---|---|---|---|
| HN180091 | 02/16/2007 03:20:00 PM | 012XX W 103RD ST | OTHER WEAPONS VIOLATION | 2232 | 22 | 21 | 73 | (41.706819022, -87.654048084) |
| HN184333 | 02/15/2007 07:00:00 PM | 093XX S WOODLAWN AVE | TELEPHONE THREAT | 413 | 4 | 8 | 47 | (41.725252492, -87.594860893) |
| HN182527 | 02/17/2007 09:00:00 PM | 042XX S COTTAGE GROVE AVE | OTHER VIOLATION | 213 | 2 | 4 | 38 | (41.81741558, -87.606719823) |
| HN183814 | 02/18/2007 10:06:37 PM | 063XX N SHERIDAN RD | TO PROPERTY | 2433 | 24 | 49 | 77 | (41.996866019, -87.655592844) |
| HN182579 | 02/18/2007 12:20:00 AM | 033XX W HURON ST | DOMESTIC BATTERY SIMPLE | 1121 | 11 | 27 | 23 | (41.893682761, -87.710701702) |
| HN182986 | 02/18/2007 10:20:00 AM | 042XX N CENTRAL AVE | OVER $500 | 1624 | 16 | 38 | 15 | (41.957385814, -87.767141739) |
| HN183716 | 02/18/2007 08:40:00 PM | 037XX S MICHIGAN AVE | | 211 | 2 | 3 | 35 | (41.827167256, -87.623160687) |
| HN184010 | 02/19/2007 02:40:00 AM | 010XX N LAWNDALE AVE | DOMESTIC BATTERY SIMPLE | 1112 | 11 | 27 | 23 | (41.89998654, -87.71890157) |
| HN181071 | 02/17/2007 02:21:00 AM | 051XX S CALUMET AVE | POSS FIREARM/AMMO:NO FOID CARD | 232 | 2 | 3 | 40 | (41.801609105, -87.617736187) |
| HN182079 | 02/17/2007 04:00:00 PM | 034XX W FLOURNOY ST | DOMESTIC BATTERY SIMPLE | 1133 | 11 | 24 | 27 | (41.872709648, -87.711929688) |
| HN184350 | 02/19/2007 12:00:00 AM | 013XX N WOLCOTT AVE | FROM BUILDING | 1424 | 14 | 1 | 24 | (41.905889056, -87.674299261) |
| HN184306 | 02/15/2007 12:01:00 AM | 001XX N PARKSIDE AVE | ILLEGAL USE CASH CARD | 1512 | 15 | 29 | 25 | (41.88301997, -87.766605275) |
| HN183370 | 02/09/2007 10:00:00 AM | 024XX W DEVON AVE | SIMPLE | 2413 | 24 | 50 | 2 | (41.99771689, -87.690448237) |
| HN183500 | 02/18/2007 05:10:00 PM | 070XX S THROOP ST | DOMESTIC BATTERY SIMPLE | 734 | 7 | 17 | 67 | (41.7658997, -87.65656296) |
| HN184055 | 02/19/2007 05:30:00 AM | 005XX W ROSCOE ST | TO RESIDENCE | 2331 | 19 | 44 | 6 | (41.943338611, -87.64332075) |
| HN184352 | 02/19/2007 10:45:00 AM | 003XX N MICHIGAN AVE | FROM BUILDING | 122 | 1 | 42 | 32 | (41.887845852, -87.624560336) |
| HN181018 | 02/17/2007 01:31:00 AM | 056XX S WABASH AVE | TO LAND | 233 | 2 | 20 | 40 | (41.792323044, -87.624025834) |
| HN182857 | 02/18/2007 07:39:41 AM | 014XX W LUNT AVE | FORCIBLE ENTRY | 2431 | 24 | 49 | 1 | (42.009107852, -87.666843608) |
| HN177373 | 02/15/2007 08:44:00 AM | 054XX S CORNELL AVE | TO VEHICLE | 2132 | 2 | 5 | 41 | (41.796263314, -87.585435453) |
| HN183280 | 01/14/2007 12:00:00 PM | 021XX W BIRCHWOOD AVE | DOMESTIC BATTERY SIMPLE | 2424 | 24 | 49 | 1 | (42.017948603, -87.683418074) |

Table 1: The City of Chicago website provides a data set containing information on crimes committed in the city from 2001 to present day.

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# 3 Time Series Analysis

The City of Chicago is divided into regions known as sides (Figure 1), where each side is comprised of several neighborhoods. There is a lot of variation in the population (Figure 2) and the number of armed robberies per capita (Figure 3) for these sides. Additionally, some sides are more residential, while others are more commercial.
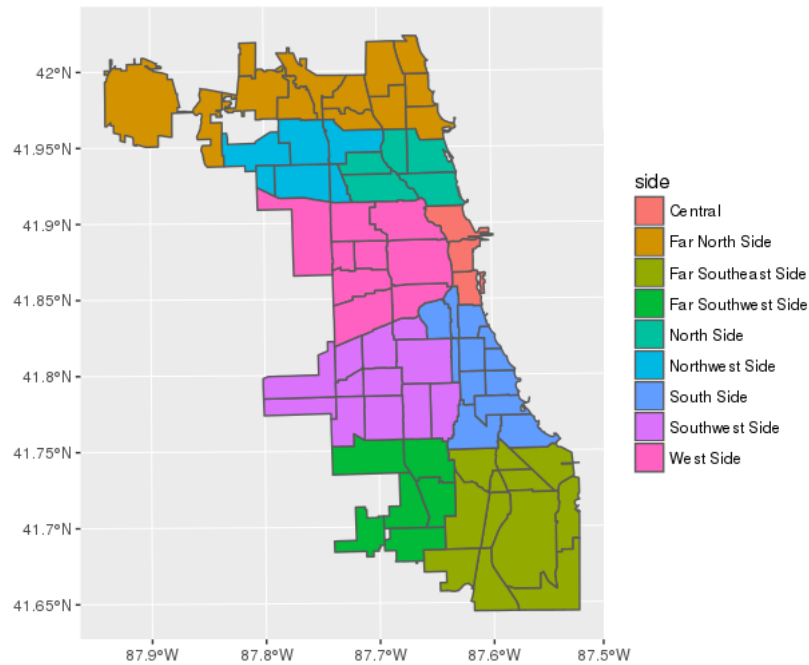


Figure 1: The "sides" of Chicago. The borders correspond to the boundaries of the community areas colored by the side.

ARIMA models were fitted to predict the counts of monthly armed robberies in each side of the city between 2003 and 2016. In order to determine the type of model, the ACF and PACF plots were examined for the data for each of the sides. For example, if there was structure in the PACF plot beyond one lag, moving average terms were added. The model residuals were also examined to ensure that there was no remaining structure in the residuals. The PACF and ACF plots for the data from the South Side are displayed below. The ACF plot showed evidence of seasonality at lag 12 (i.e. yearly trends). After lag 1, there was no large values for the PACF, so no moving average terms were included in the model.
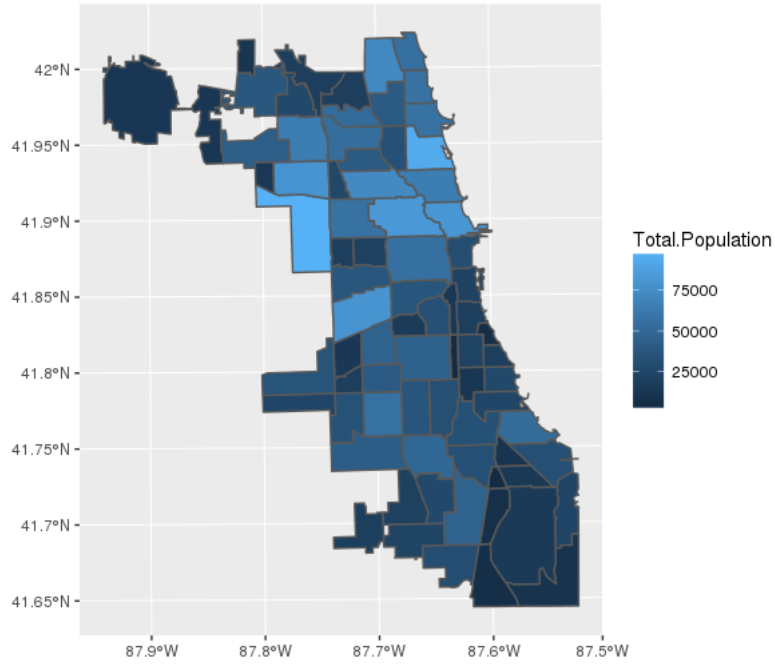
Figure 2: The population distribution of the "sides" of Chicago. The borders correspond to the boundaries of the community areas.
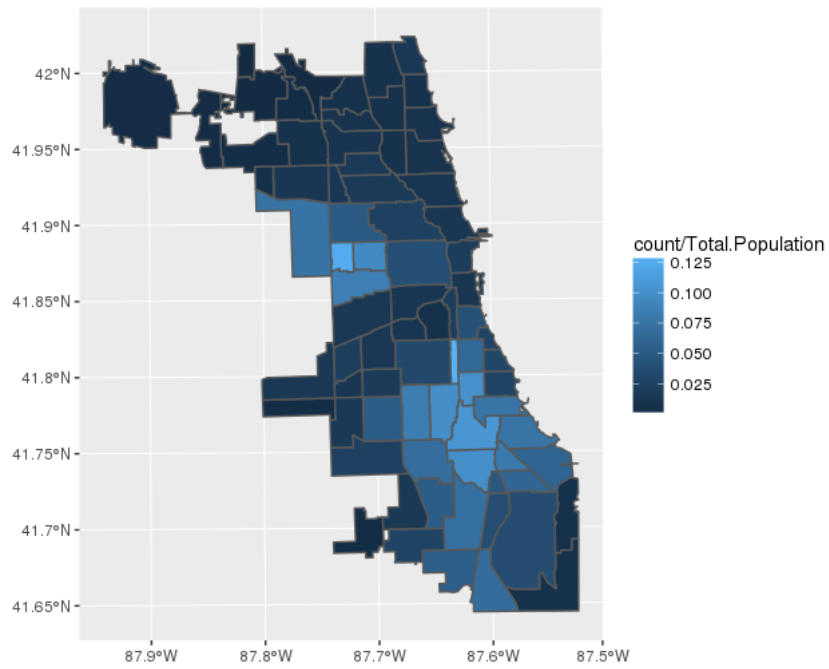


Figure 3: The number of armed robberies per capita for the "sides" of Chicago between 2003 and 2016. The borders correspond to the boundaries of the community areas.

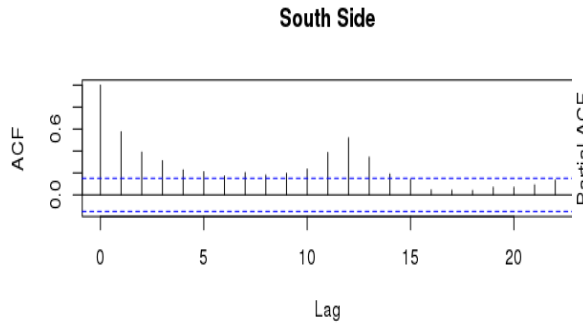South Side                              South Side

Figure 4: ACF plot for the number of monthly armed robberies in the South Side of Chicago between 2003 and 2016.
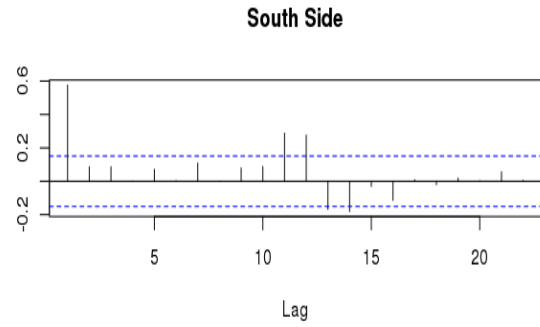
Figure 5: PACF plot for the number of monthly armed robberies in the South Side of Chicago between 2003 and 2016.

Based on the ACF Figure 6 and PACF Figure 3 plots, an AR(4) model was fit with a seasonal component with period twelve. The residuals plot for this model did not display any remaining structure in the data and the coefficients are in Table 3.



Figure 6: ACF plot of the residuals of an AR(4) model with a period twelve seasonal component fit to the monthly count of armed robberies for the South Side.
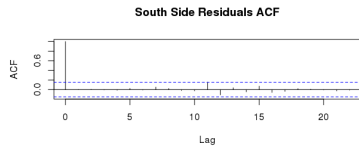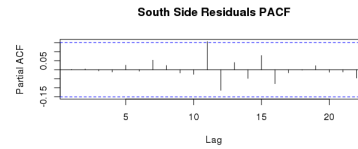
Figure 7: PACF plot of the residuals of an AR(4) model with a period twelve seasonal component fit to the monthly count of armed robberies for the South Side.

|  | ar1 | ar2 | ar3 | ar4 | sar1 |
|---|---|---|---|---|---|
| Coefficient | 0.3850 | 0.1328 | 0.0825 | 0.0167 | 0.4784 |
| Standard Error | 0.0793 | 0.0832 | 0.0824 | 0.0771 | 0.0708 |

Table 2: Summary of model fit for the AR(4) with period 12 seasonal component fit to the monthly count of armed robberies for the South Side.

The coefficient estimates for all of the different sides were very similar. While some sides displayed evidence of higher order autoregressive structure or the addition of moving average terms, as compared to the South Side, all sides had a clear period 12 seasonal component, indicating strong yearly trends for all sides of the city. The coefficient estimates were positive for the autoregressive terms, indicating that there was a positive correlation between the amount of monthly armed robberies over time. Plots of the various model fits can be found in subsection 5.1. It is interesting that although the sides of Chicago are quite diverse in terms of population and demographics, as well as the number of monthly armed robberies, the temporal trends for all of the sides are very similar. Although the count of the monthly armed robberies differs by side of the city, the overall temporal trend is the same across Chicago and has a strong yearly, autoregressive trend.

# 4 Spatial Models

## 4.1 Introduction

The City of Chicago is comprised of 77 distinct community areas. We predict for counts of armed robbery in each area using a Bayesian Spatial Latent Gaussian Process Poisson Regression Model (BSLGPPR) and a 100 explanatory variables provided by Chicago gathered from a range of years within that of the armed robbery data. We do make the assumption that these variables have not changed much over the next/previous few years and remain applicable. The explanatory variables come from 8 different datasets, average electricity usage, average gas usage, counts of graffiti removal, public health statistics, socioeconomic indicators, vacant properties, and demographics data.

Since we have numerous explanatory variables that range from demographic information to counts of graffiti art, we want to narrow down the number of variables to improve the model's prediction accuracy and interpretability. A popular frequentist method is the penalized LASSO regression; however, it does not take into account spatial information. Our model, the BSLGPPR, will simulate a LASSO regression while also modeling spatial random effects.

As the response variable of our data are counts of armed robbery in community areas, we model our observations $\{y_i\}_1^N$, $N = 77$, with a Poisson distribution.

$$y_i \sim \text{Poisson}(\lambda_i) \tag{1}$$

We know that $\lambda_i$ must be positive, which is why we let it equal to the exponential of $\mathbf{X}\beta$. $\beta$ are the coefficients for the explanatory variables and the intercept, which comprises the design matrix $\mathbf{X}$.

$$\log(\boldsymbol{\lambda}) = \mathbf{X}\beta \tag{2}$$

Equation 2 is for the LASSO regression, but we will add another variable $\omega_i$ to model random spatial effect in the BSLGPPR model.

$$\log(\boldsymbol{\lambda}) = \mathbf{X}\beta + \boldsymbol{\omega} \tag{3}$$

## 4.2 The LASSO Model

Our first model comprises of a simple penalized LASSO regression. Given the positive value of Moran's I, 0.5118399, this model is highly unlikely to outperform one that takes into account the spatial nature of crime. However, we implement this model as a baseline in order to illustrate why the BSLGPPR model performs better.

In this model, without the random spatial effect, we do make the assumption that the observations are independent of one another.

From Equation 2, it is simple to realize that

$$\boldsymbol{\lambda} = e^{\beta' \mathbf{X}}$$

. Given a set of parameters $\beta$, and explanatory variables $\mathbf{X}$, we observe the counts of armed robbery $\mathbf{Y}$ with probability

$$p(y_1, ..., y_N | \mathbf{x}_1, ..., \mathbf{x}_N, \beta) = \prod_{i=1}^{N} \frac{e^{y_i \beta' \mathbf{x}_i} e^{-e^{\beta' \mathbf{x}_i}}}{y_i!} \tag{4}$$

Equation 4 can be obtained by plugging Equation 2 into the Poisson probability distribution.

We then want to use the maximum likelihood method to find a set of $\beta$ that will maximize the likelihood, Equation 4 which is the same as maximizing the log-likelihood:

$$l(\beta | \mathbf{X}, \mathbf{Y}) = \sum_{i=1}^{N} \left( y_i (\beta' \mathbf{x}_i) - e^{\beta' x_i} \right) \tag{5}$$

To implement the penalized LASSO regression, we instead optimize the penalized log-likelihood:

$$\min_{\beta} -\frac{1}{N} l(\beta | \mathbf{X}, \mathbf{Y}) + \lambda \frac{1}{2} \left( (1 - \alpha) \sum_{i=1}^{N} \beta_i^2 + \alpha \sum_{i=1}^{N} |\beta_i| \right) \tag{6}$$

and set $\alpha = 1$.

This method will allow us to obtain more accurate predictions than regular OLS and perform variable selection to prevent overfitting and for interpretability purposes.

### 4.3    The Bayesian Spatial Latent Gaussian Process Poisson Regression Model

Our second model uses a double exponential or Laplace prior to emulate the LASSO penalized regression model as the distribution sharply peaks at zero; concentrating the probability mass at zero. While this prior will not cause our coefficients to go to zero as in the case of a LASSO–instead behaving more like Ridge regression–we get around this by constructing 95 percent credible intervals around the coefficients and finding the ones that contain zero.

In our Bayesian model, we use the same data as in subsection 4.2 and supplement in spatial data in terms of spatial polygons for the 77 areas.

For our model, we take Equation 1 and Equation 3 and further specify by setting:

$$\beta_j \stackrel{iid}{\sim} \text{Laplace}(0, \eta)$$
$$\boldsymbol{\omega} \sim \text{MVN}(\boldsymbol{0}, \tau(D - \phi W))$$
$$\tau \sim \text{Gamma}(2, 2)$$
$$\phi \sim \text{Unif}(0, 0.99)$$
$$\eta \sim \text{Unif}(0.001, 10)$$

where $\{D : d_{\{jj\}}\} = $ total number of neighboring community areas for community area j$|j \in 1...77\}$

where $\{W : w_{\{jk\}}\} = $ whether community area j shares boundaries with community area k$|j, k \in 1...77\}$

Like before, we say that the armed robbery data can be modeled using a Poisson distribution with $\lambda_i$. We know that $\lambda_i$ must be positive, which is why we let it equal to the exponential of $\mathbf{X}\beta + \omega_i$. $\beta$ are the coefficients for each explanatory variable $\mathbf{X}$ and the intercept. We model the random spatial effect by putting a multivariate gaussian prior on $\omega_i$ and setting the mean to zero,we expect the average effect to be 0, and a correlation matrix $\tau(D - \phi W))$, we believe community areas to be affected by neighboring community areas and the total number of neighboring community areas, which is then scaled by $\tau$ and $\phi$. We set $\tau$ to have a Gamma(2,2) prior because we believe $\tau$ is positive and also heavily concentrated between 0 and 4. $\phi$ has a Unif(0, 0.99) prior to allow for equal probability for any value within the specified range; as we are not biased towards any weight for W. The $\beta$s are iid Laplace to emulate a penalized LASSO regression. We set $\eta$ to have a Unif(0.001, 10) distribution because we believe that is how concentrated the $\beta$'s will be around the mean, 0; the smaller the $\eta$ the more heavily concentrated at the mean.

### 4.4    Results

$\beta$ coefficients for the two models can be seen in Table 13 and Table 14 along with 95% credible intervals for the BSLGPPR model. To summarize, the LASSO model selects 30 variables whereas BSLGPPR selects 15 variables as seen in Table 3 and Table 4. Predictions are also more accurate as seen in Figure 8; the residuals for the BSLGPPR model are minute compared to that of the LASSO model as the LASSO scale would be approximately 100 times wider than that of the BSLGPPR model. While it seems the predictions in comparison to that of other community areas are similar between the two models, it does not change that BSLGPPR is more accurate. Take a community area such as Austin, predicted to have the highest amount of armed robberies for both models, yet the predicted amount differs by approximately 1000 counts–which is very significant in this context.

### 4.5    Conclusion

Examining our coefficients, given the much lower RMSE value for our BSLGPPR model, and the spatial nature of the data, it makes sense to only consider these coefficients.

| Variable | Lasso |
|---|---|
| Intercept | 6.5489 |
| Male: 65 and 66 years | -0.3789 |
| Not Hispanic or Latino, Black or African American alone | 0.2773 |
| Assault (Homicide) | 0.2175 |
| Unemployment | -0.2116 |
| Infant Mortality Rate | 0.2030 |
| Vacant Housing Units | 0.1868 |
| Female: 30 to 34 years | 0.1732 |
| Prenatal Care Beginning in First Trimester | -0.1557 |
| Breast cancer in females | 0.1407 |
| N_Graffiti | 0.1310 |
| Hispanic or Latino | 0.1115 |
| Female: 22 to 24 years | 0.1054 |
| Low Birth Weight | 0.0916 |
| Female: 80 to 84 years | 0.0863 |
| Female: 18 and 19 years | 0.0851 |
| PERCENT AGED 16+ UNEMPLOYED | 0.0847 |
| Tuberculosis | 0.0790 |
| Female: 15 to 17 years | 0.0785 |
| Female: 5 to 9 years | 0.0642 |
| Crowded Housing | -0.0503 |
| Firearm-related | 0.0400 |
| Female: 21 years | 0.0381 |
| Female: 85 years and over | 0.0377 |
| Stroke (Cerebrovascular Disease) | -0.0358 |
| Prostate Cancer in Males | 0.0227 |
| Colorectal Cancer | 0.0124 |
| vacantLots | -0.0080 |
| Not Hispanic or Latino, Asian alone | -0.0045 |
| N_Aff_Housing | 0.0006 |

Table 3: LASSO model's non-zero Beta Coefficients sorted from Most to Least Impact

In particular, we note that there is a strong negative relationship between the number of females between 10 to 14 years. One potential hypothesis for this is that families with younger female children are more likely to live in safe neighborhoods or gated communities. It is also interesting to note that the rate of cancer has a high positive relationship with the number of armed robberies. In Chicago, many of the industrial areas surrounding Lake Michigan have are polluted with heavy metals, often leading to higher rates of cancer. [1]

Finally, we note that unemployment appears to have a negative relationship with the number of armed robberies. This definitely warrants further investigation. One possible explanation is that the rate of unemployment only includes those that are actively seeking work. [10] As a result, many of the poorest neighborhoods in Chicago do not have particularly high unemployment rates because there simply are not enough jobs to go around, and with high levels of gang activity, anyone in a gang is unlikely to be counted as unemployed.

While it is not possible to determine a causal relationship from this model, further work would explore potential naturally occurring controlled experiments to determine causality. For example, if we find a relationship between crime and pollution levels, policies within community areas that reduce the levels of pollution could be used to explore the changes in crime rates with these changes

| 2.5% | 97.5% | Spatial | Variable |
|---|---|---|---|
| 6.2136 | 6.2683 | 6.2427 | Intercept |
| -0.8244 | -0.3868 | -0.5845 | Unemployment |
| -0.7821 | -0.1529 | -0.5485 | Male: 45 to 49 years |
| -0.9097 | -0.1008 | -0.4947 | Female: 10 to 14 years |
| 0.1699 | 0.5196 | 0.3433 | PERCENT AGED 16+ UNEMPLOYED |
| -0.5641 | -0.0527 | -0.2933 | Male: 65 and 66 years |
| 0.1618 | 0.4959 | 0.2893 | Cancer (All Sites) |
| 0.0753 | 0.5511 | 0.2888 | Male: 10 to 14 years |
| 0.1335 | 0.3318 | 0.2309 | Infant Mortality Rate |
| 0.0626 | 0.3982 | 0.2145 | Birth Rate |
| -0.3259 | -0.0923 | -0.2129 | Prenatal Care Beginning in First Trimester |
| 0.0968 | 0.3364 | 0.1923 | N_Graffiti |
| 0.0697 | 0.2227 | 0.1423 | Breast cancer in females |
| -0.2459 | -0.0209 | -0.1398 | Not Hispanic or Latino, Asian alone |
| 0.0144 | 0.2186 | 0.1282 | Tuberculosis |
| 0.0107 | 0.2456 | 0.1021 | Low Birth Weight |

Table 4: BSLGPPR model's Beta Coefficients that did not contain zero in their 95% credible interval, sorted from Most to Least Impact

in pollution levels. Further work will explore these type of controlled experiments based on the most important features found through our spatial model.
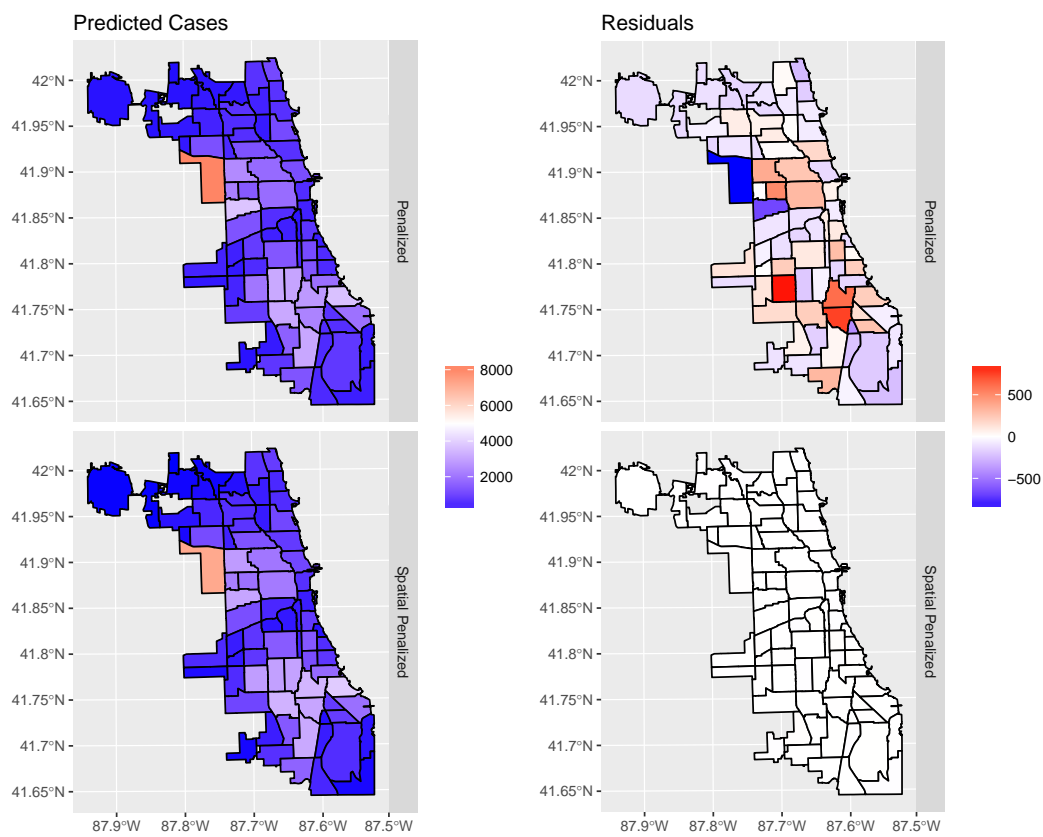
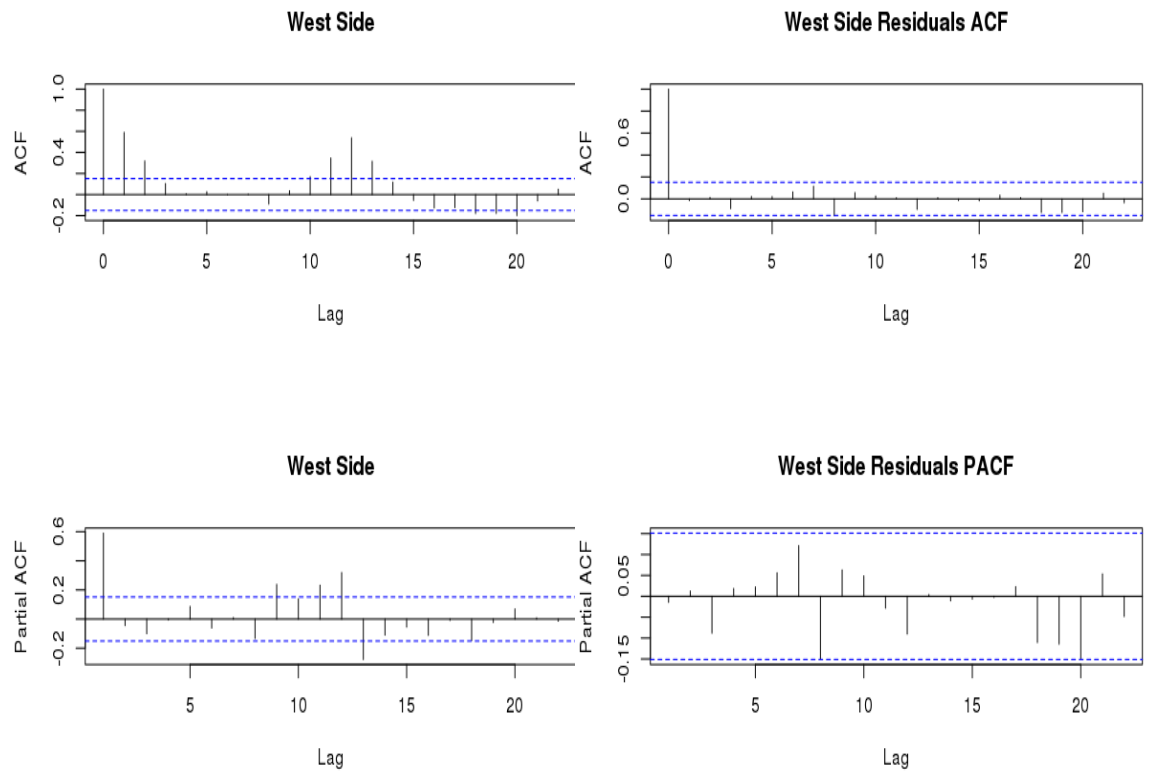Figure 8: Comparison of Two Model Predictions and Residuals

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# 5 Appendix

## 5.1 Time Series Modeling Plots

### 5.1.1 West Side - ARIMA(2,0,0) x (1,0,0)[12]



|                | ar1    | ar2    | sar1   |
|----------------|--------|--------|--------|
| Coefficient    | 0.5742 | 0.0329 | 0.5735 |
| Standard Error | 0.0791 | 0.0796 | 0.0643 |

Table 5: Summary of model fit for the AR(2) with period 12 seasonal component fit to the monthly count of armed robberies for the West Side.

### 5.1.2 Southwest Side - ARIMA(12,0,0) x (1,0,0)[12]
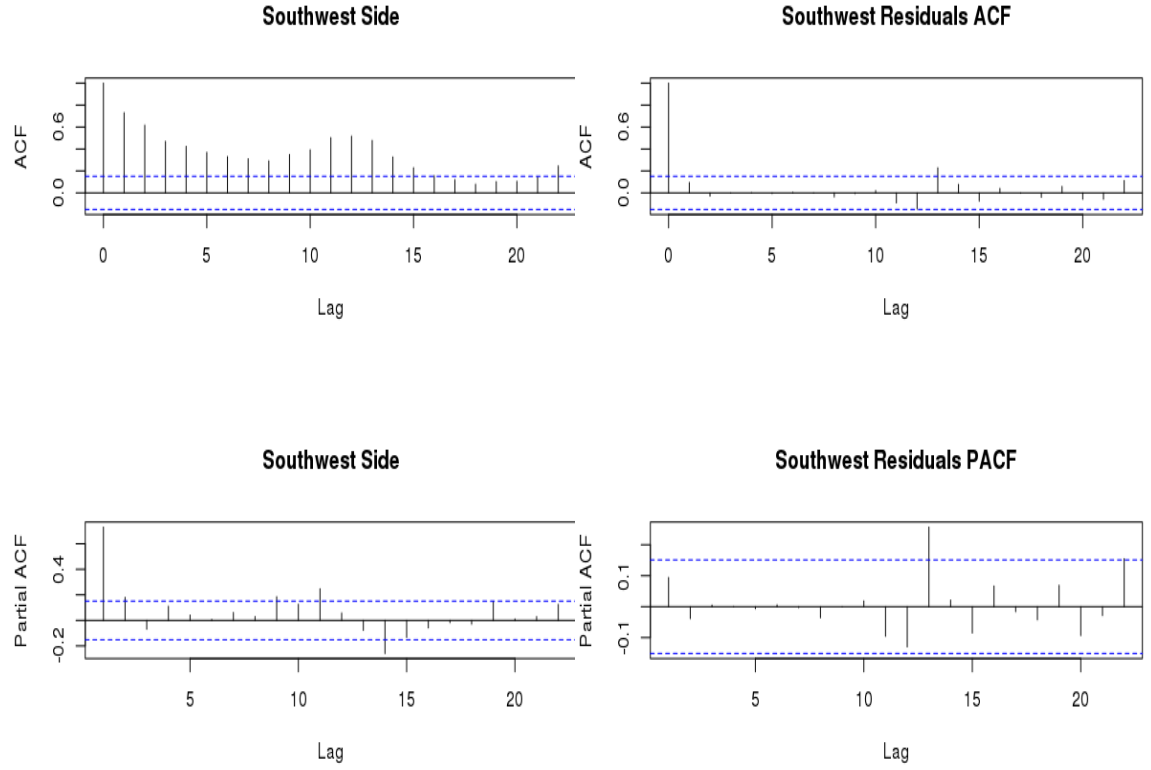


| | ar1 | ar2 | ar3 | ar4 | ar5 | ar6 | ar7 |
|---|---|---|---|---|---|---|---|
| Coefficient | 0.3718 | 0.2471 | -0.0041 | 0.1178 | 0.0534 | 0.0521 | -0.0722 |
| Standard Error | 0.0861 | 0.0791 | 0.0837 | 0.0811 | 0.0829 | 0.0844 | 0.0820 |
| | | ar8 | ar9 | ar10 | ar11 | ar12 | sar1 |
| Coefficient | | -0.0419 | 0.0943 | -0.0330 | 0.1937 | -0.3336 | 0.6148 |
| Standard Error | | 0.0819 | 0.0810 | 0.0827 | 0.0843 | 0.0978 | 0.1077 |

Table 6: Summary of model fit for the AR(12) with period 12 seasonal component fit to the monthly count of armed robberies for the Southwest Side.

### 5.1.3   Far Southeast Side - ARIMA(12,0,0) x (1,0,0)[12]
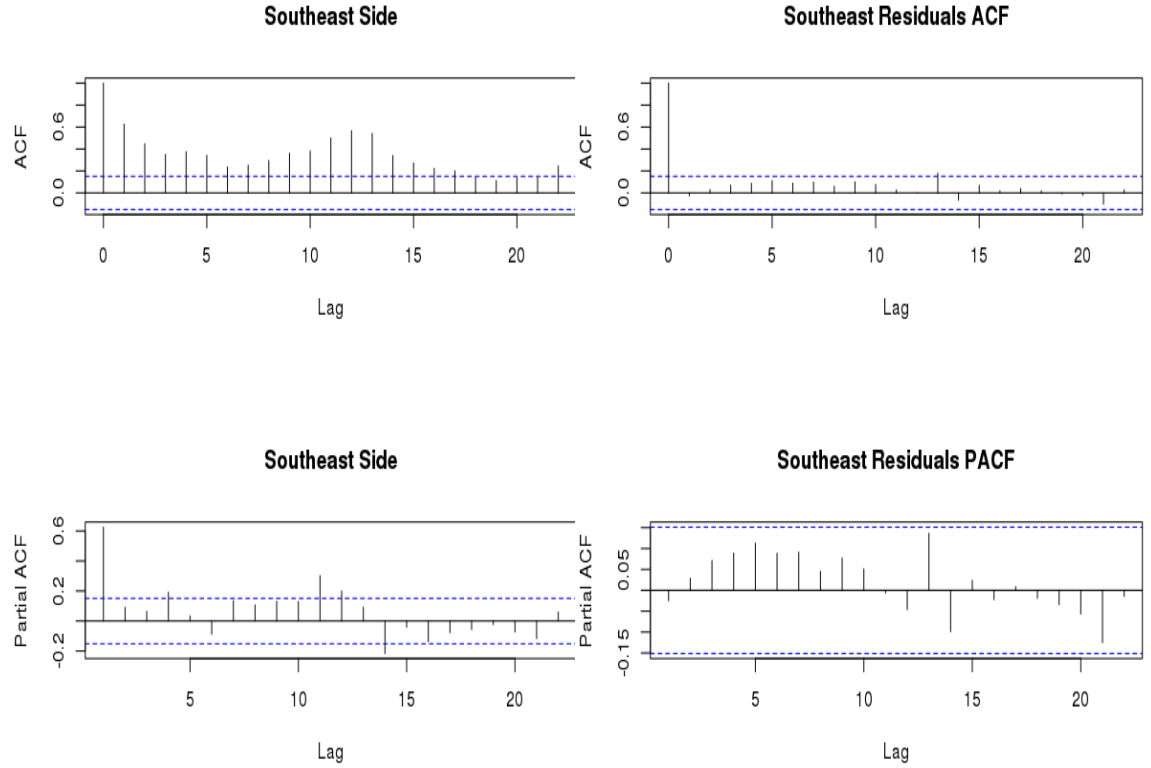


| | ar1 | ar2 | ar3 | ar4 | ar5 | ar6 | ar7 |
|---|---|---|---|---|---|---|---|
| Coefficient | 0.3841 | 0.0168 | -0.0954 | 0.1271 | 0.1040 | -0.1575 | -0.0059 |
| Standard Error | 0.0742 | 0.0832 | 0.0797 | 0.0800 | 0.0796 | 0.0791 | 0.0815 |
| | | ar8 | ar9 | ar10 | ar11 | ar12 | sar1 |
| Coefficient | | 0.0193 | 0.0552 | -0.0223 | 0.2122 | 0.2868 | -0.0748 |
| Standard Error | | 0.0802 | 0.0837 | 0.0795 | 0.0827 | 0.1119 | 0.1373 |

Table 7: Summary of model fit for the AR(12) with period 12 seasonal component fit to the monthly count of armed robberies for the Far Southeast Side.

### 5.1.4  Northwest Side - ARIMA(3,0,0) x (1,0,0)[12]
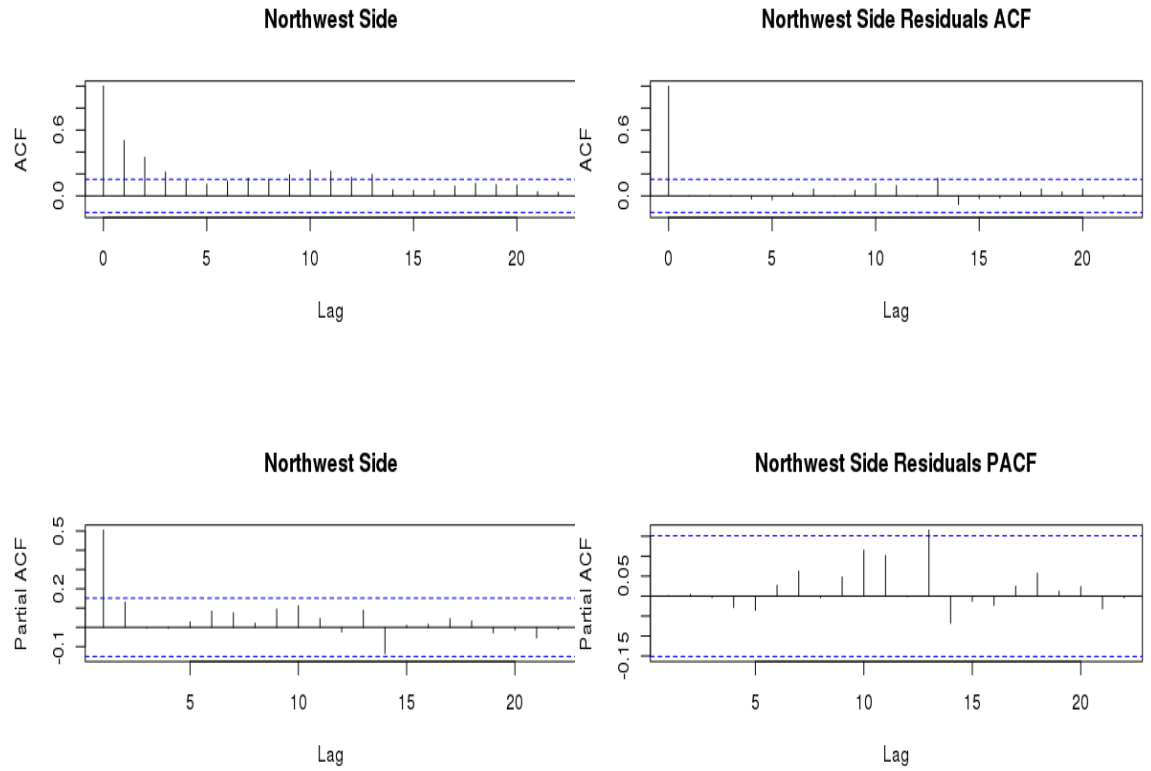




|                | ar1    | ar2    | ar3    | sar1   |
|----------------|--------|--------|--------|--------|
| Coefficient    | 0.4330 | 0.1290 | 0.0021 | 0.0169 |
| Standard Error | 0.0798 | 0.0842 | 0.0782 | 0.0848 |

Table 8: Summary of model fit for the AR(3) with period 12 seasonal component fit to the monthly count of armed robberies for the Northwest Side.

### 5.1.5 North Side - ARIMA(3,0,0) x (1,0,0)[12]



|                | ar1    | ar2    | ar3    | sar1   |
|----------------|--------|--------|--------|--------|
| Coefficient    | 0.2810 | 0.2050 | 0.0014 | 0.2441 |
| Standard Error | 0.0825 | 0.0816 | 0.0809 | 0.0871 |

Table 9: Summary of model fit for the AR(3) with period 12 seasonal component fit to the monthly count of armed robberies for the North Side.

## 5.1.6 Far Southwest Side - ARIMA(5,0,0) x (1,0,0)[12]
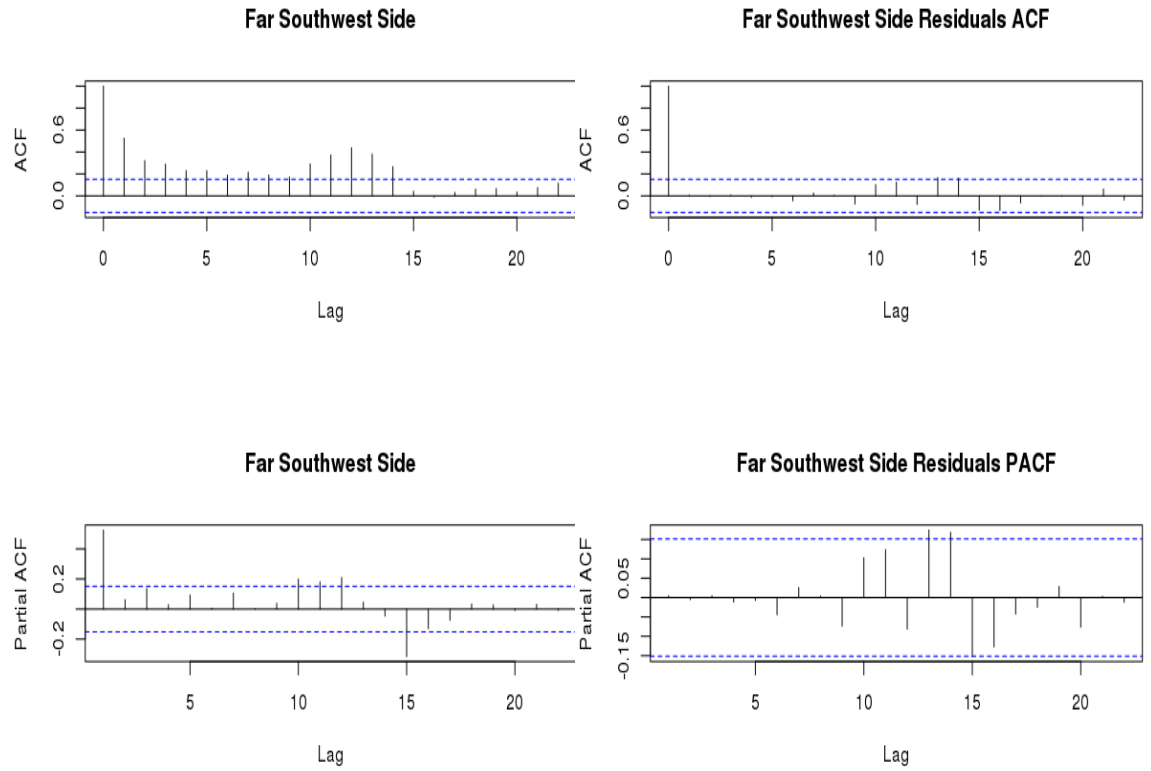


|                | ar1    | ar2     | ar3    | ar4    | ar5    | sar1   |
|----------------|--------|---------|--------|--------|--------|--------|
| Coefficient    | 0.3477 | -0.0629 | 0.2363 | 0.0084 | 0.0928 | 0.3577 |
| Standard Error | 0.0825 | 0.0825  | 0.0823 | 0.0821 | 0.0774 | 0.0819 |

Table 10: Summary of model fit for the AR(5) with period 12 seasonal component fit to the monthly count of armed robberies for the Far Southwest Side.
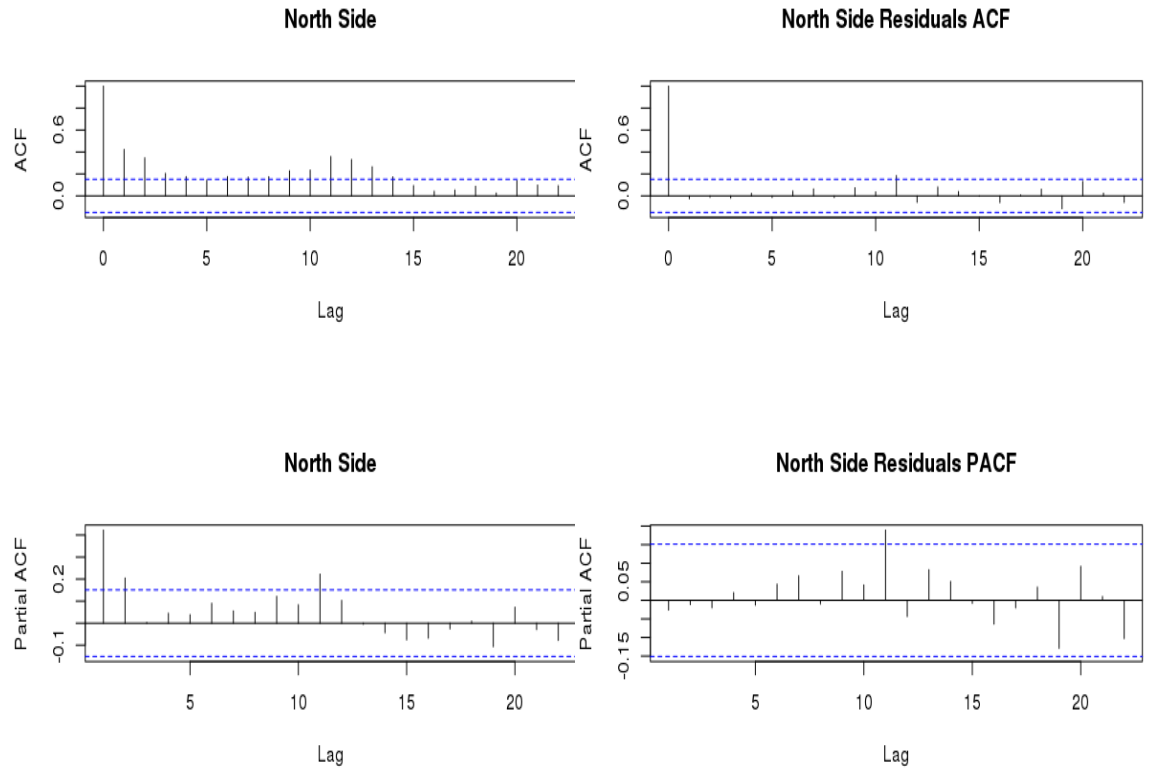
### 5.1.7 Far North Side - ARIMA(3,0,0) x (1,0,0)[12]
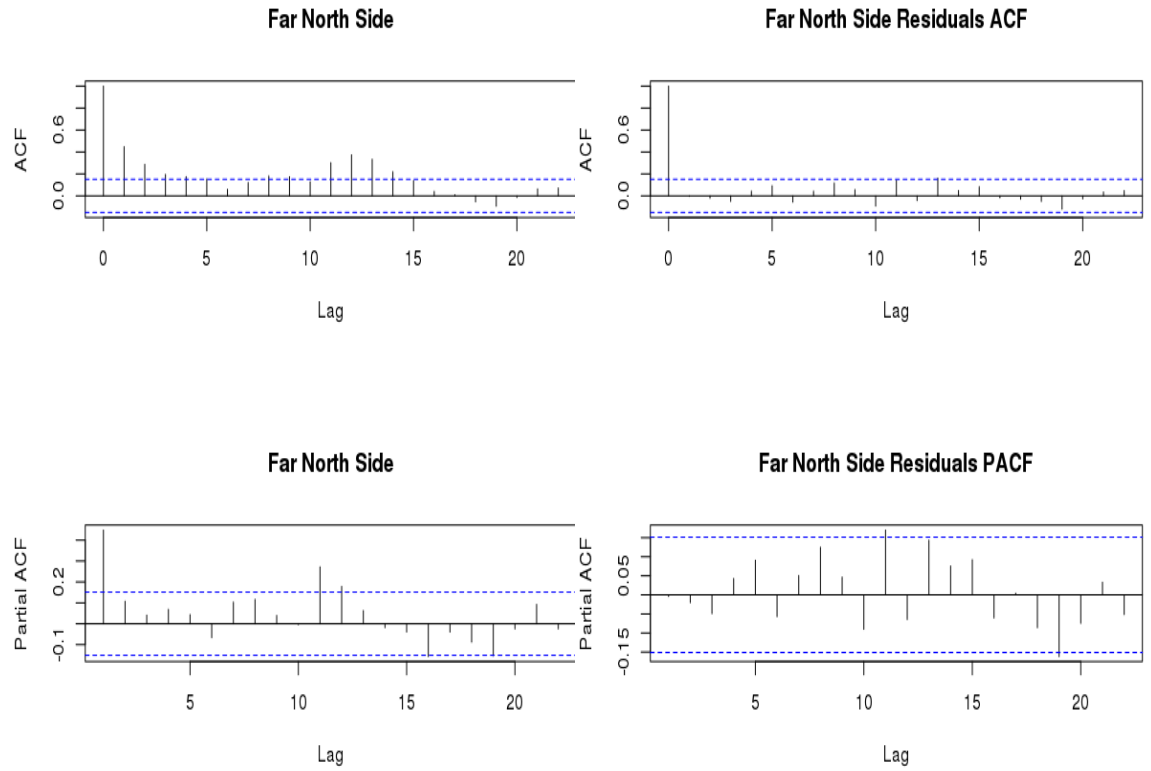


|                | ar1    | ar2    | ar3    | sar1   |
|----------------|--------|--------|--------|--------|
| Coefficient    | 0.3000 | 0.1374 | 0.0190 | 0.2987 |
| Standard Error | 0.0823 | 0.0805 | 0.0781 | 0.0848 |

Table 11: Summary of model fit for the AR(3) with period 12 seasonal component fit to the monthly count of armed robberies for the Far North Side.

### 5.1.8 Central - ARIMA(2,0,0) x (1,0,0)[12]

**Central**



**Central Residuals ACF**



**Central**



**Central Residuals PACF**



|                | ar1    | ar2    | sar1   |
|----------------|--------|--------|--------|
| Coefficient    | 0.3372 | 0.1944 | 0.2026 |
| Standard Error | 0.0793 | 0.0773 | 0.0921 |

Table 12: Summary of model fit for the AR(2) with period 12 seasonal component fit to the monthly count of armed robberies for the Central Side.
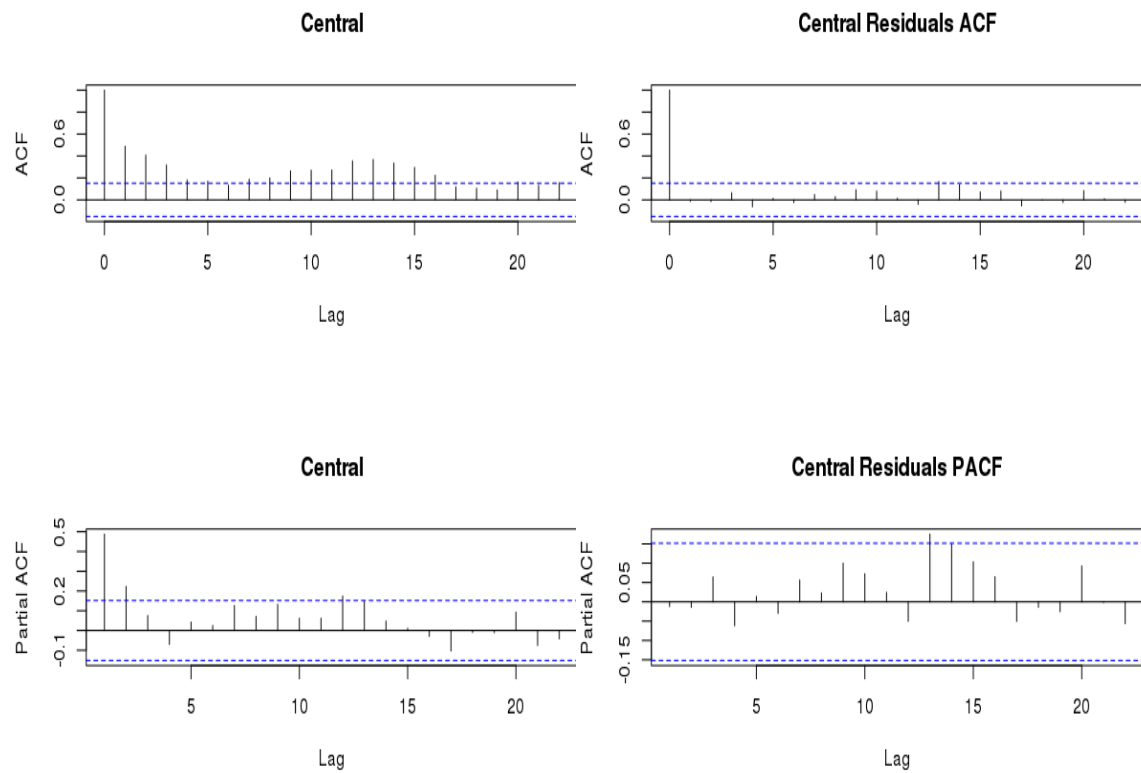
## 5.2 Spatial Analysis

| Variable | Lasso | 2.5% | 97.5% | Spatial | IncludeZero |
|---|---|---|---|---|---|
| Intercept | 6.5489 | 6.2136 | 6.2683 | 6.2427 | FALSE |
| KWH Total SQFT | 0.0000 | -0.1712 | 0.4157 | 0.0727 | TRUE |
| THERMS Total SQFT | 0.0000 | -0.2902 | 0.3763 | 0.0674 | TRUE |
| N_Graffiti | 0.1310 | 0.0968 | 0.3364 | 0.1923 | FALSE |
| Birth Rate | 0.0000 | 0.0626 | 0.3982 | 0.2145 | FALSE |
| General Fertility Rate | 0.0000 | -0.3869 | 0.0174 | -0.1396 | TRUE |
| Low Birth Weight | 0.0916 | 0.0107 | 0.2456 | 0.1021 | FALSE |
| Prenatal Care Beginning in First Trimester | -0.1557 | -0.3259 | -0.0923 | -0.2129 | FALSE |
| Preterm Births | 0.0000 | -0.1675 | 0.0465 | -0.0610 | TRUE |
| Teen Birth Rate | 0.0000 | -0.1547 | 0.1216 | -0.0162 | TRUE |
| Assault (Homicide) | 0.2175 | -0.1223 | 0.3060 | 0.0898 | TRUE |
| Breast cancer in females | 0.1407 | 0.0697 | 0.2227 | 0.1423 | FALSE |
| Cancer (All Sites) | 0.0000 | 0.1618 | 0.4959 | 0.2893 | FALSE |
| Colorectal Cancer | 0.0124 | -0.0272 | 0.1851 | 0.0822 | TRUE |
| Diabetes-related | 0.0000 | -0.1356 | 0.0732 | -0.0433 | TRUE |
| Firearm-related | 0.0400 | -0.0884 | 0.1132 | 0.0265 | TRUE |
| Infant Mortality Rate | 0.2030 | 0.1335 | 0.3318 | 0.2309 | FALSE |
| Lung Cancer | 0.0000 | -0.1050 | 0.1438 | 0.0014 | TRUE |
| Prostate Cancer in Males | 0.0227 | -0.0799 | 0.1437 | 0.0198 | TRUE |
| Stroke (Cerebrovascular Disease) | -0.0358 | -0.1426 | 0.0592 | -0.0379 | TRUE |
| Tuberculosis | 0.0790 | 0.0144 | 0.2186 | 0.1282 | FALSE |
| Below Poverty Level | 0.0000 | -0.0601 | 0.2703 | 0.0843 | TRUE |
| Crowded Housing | -0.0503 | -0.3545 | 0.0036 | -0.1928 | TRUE |
| Dependency | 0.0000 | -0.0464 | 0.2258 | 0.0723 | TRUE |
| No High School Diploma | 0.0000 | -0.1632 | 0.3010 | 0.0759 | TRUE |
| Per Capita Income | 0.0000 | -0.2785 | 0.2422 | -0.0064 | TRUE |
| Unemployment | -0.2116 | -0.8244 | -0.3868 | -0.5845 | FALSE |
| N_Aff_Housing | 0.0006 | -0.0934 | 0.0205 | -0.0323 | TRUE |
| PERCENT OF HOUSING CROWDED | 0.0000 | -0.1809 | 0.0931 | -0.0349 | TRUE |
| PERCENT HOUSEHOLDS BELOW POVERTY | 0.0000 | -0.2042 | 0.2440 | -0.0041 | TRUE |
| PERCENT AGED 16+ UNEMPLOYED | 0.0847 | 0.1699 | 0.5196 | 0.3433 | FALSE |
| PERCENT AGED 25+ WITHOUT HIGH SCHOOL DIPLOMA | 0.0000 | -0.2138 | 0.4319 | 0.1477 | TRUE |
| PERCENT AGED UNDER 18 OR OVER 64 | 0.0000 | -0.2190 | 0.2157 | -0.0505 | TRUE |
| PER CAPITA INCOME | 0.0000 | -0.1572 | 0.1933 | 0.0253 | TRUE |
| HARDSHIP INDEX | 0.0000 | -0.1290 | 0.6274 | 0.1752 | TRUE |
| vacantLots | -0.0080 | -0.0200 | 0.0946 | 0.0451 | TRUE |
| Total Population | 0.0000 | -0.0719 | 0.3466 | 0.1129 | TRUE |
| Not Hispanic or Latino, White alone | 0.0000 | -0.3291 | 0.1993 | -0.0750 | TRUE |
| Not Hispanic or Latino, Black or African American alone | 0.2773 | -0.1242 | 0.1845 | 0.0646 | TRUE |
| Not Hispanic or Latino, American Indian and Alaska Native alone | 0.0000 | -0.1491 | 0.2238 | 0.0764 | TRUE |
| Not Hispanic or Latino, Asian alone | -0.0045 | -0.2459 | -0.0209 | -0.1398 | FALSE |
| Not Hispanic or Latino, Native Hawaiian and Other Pacific Islander alone | 0.0000 | -0.0508 | 0.0893 | 0.0065 | TRUE |
| Not Hispanic or Latino, Some Other Race alone | 0.0000 | -0.1073 | 0.3309 | 0.1343 | TRUE |
| Not Hispanic or Latino, Two or More Races | 0.0000 | -0.3185 | 0.3276 | 0.0182 | TRUE |
| Hispanic or Latino | 0.1115 | -0.2077 | 0.1797 | 0.0237 | TRUE |
| Male: Under 5 years old | 0.0000 | -0.1909 | 0.1494 | -0.0237 | TRUE |
| Male: 5 to 9 years | 0.0000 | -0.2622 | 0.0710 | -0.0919 | TRUE |
| Male: 10 to 14 years | 0.0000 | 0.0753 | 0.5511 | 0.2888 | FALSE |
| Male: 15 to 17 years | 0.0000 | -0.3138 | 0.2186 | 0.0197 | TRUE |
| Male: 18 and 19 years | 0.0000 | -0.0289 | 0.7760 | 0.3415 | TRUE |
| Male: 20 years | 0.0000 | -0.0030 | 0.3619 | 0.1537 | TRUE |

Table 13: Beta Coefficients for LASSO and BSLGPPR Models.

| Variable | Lasso | 2.5% | 97.5% | Spatial | IncludeZero |
|---|---|---|---|---|---|
| Male: 21 years | 0.0000 | -0.3656 | 0.1339 | -0.0838 | TRUE |
| Male: 22 to 24 years | 0.0000 | -0.1454 | 0.3723 | 0.0717 | TRUE |
| Male: 25 to 29 years | 0.0000 | -0.1612 | 0.4841 | 0.1711 | TRUE |
| Male: 30 to 34 years | 0.0000 | -0.4044 | 0.1591 | -0.0959 | TRUE |
| Male: 35 to 39 years | 0.0000 | -0.4585 | 0.3307 | 0.0278 | TRUE |
| Male: 40 to 44 years | 0.0000 | -0.2925 | 0.2505 | 0.0403 | TRUE |
| Male: 45 to 49 years | 0.0000 | -0.7821 | -0.1529 | -0.5485 | FALSE |
| Male: 50 to 54 years | 0.0000 | -0.2311 | 0.2038 | -0.0092 | TRUE |
| Male: 55 to 59 years | 0.0000 | -0.1085 | 0.5342 | 0.1661 | TRUE |
| Male: 60 and 61 years | 0.0000 | -0.1383 | 0.3300 | 0.0697 | TRUE |
| Male: 62 to 64 years | 0.0000 | -0.4629 | 0.0427 | -0.2165 | TRUE |
| Male: 65 and 66 years | -0.3789 | -0.5641 | -0.0527 | -0.2933 | FALSE |
| Male: 67 to 69 years | 0.0000 | -0.2136 | 0.2511 | 0.0377 | TRUE |
| Male: 70 to 74 years | 0.0000 | -0.4171 | 0.0526 | -0.1750 | TRUE |
| Male: 75 to 79 years | 0.0000 | -0.2765 | 0.1980 | -0.0323 | TRUE |
| Male: 80 to 84 years | 0.0000 | -0.1820 | 0.1216 | -0.0021 | TRUE |
| Male: 85 years and over | 0.0000 | -0.1266 | 0.2376 | 0.0535 | TRUE |
| Female: Under 5 years old | 0.0000 | -0.0854 | 0.3244 | 0.0571 | TRUE |
| Female: 5 to 9 years | 0.0642 | -0.2919 | 0.4038 | 0.0265 | TRUE |
| Female: 10 to 14 years | 0.0000 | -0.9097 | -0.1008 | -0.4947 | FALSE |
| Female: 15 to 17 years | 0.0785 | -0.1623 | 0.2829 | 0.0487 | TRUE |
| Female: 18 and 19 years | 0.0851 | -0.2976 | 0.4667 | 0.0772 | TRUE |
| Female: 20 years | 0.0000 | -0.3636 | 0.1191 | -0.1461 | TRUE |
| Female: 21 years | 0.0381 | -0.2372 | 0.1521 | -0.0438 | TRUE |
| Female: 22 to 24 years | 0.1054 | -0.2446 | 0.1472 | -0.0319 | TRUE |
| Female: 25 to 29 years | 0.0000 | -0.2606 | 0.2080 | -0.0201 | TRUE |
| Female: 30 to 34 years | 0.1732 | -0.5229 | 0.2026 | -0.1613 | TRUE |
| Female: 35 to 39 years | 0.0000 | -0.1611 | 0.4163 | 0.1265 | TRUE |
| Female: 40 to 44 years | 0.0000 | -0.0885 | 0.4475 | 0.1260 | TRUE |
| Female: 45 to 49 years | 0.0000 | -0.0847 | 0.3460 | 0.1258 | TRUE |
| Female: 50 to 54 years | 0.0000 | -0.2909 | 0.1965 | -0.0274 | TRUE |
| Female: 55 to 59 years | 0.0000 | -0.1331 | 0.2360 | 0.0520 | TRUE |
| Female: 60 and 61 years | 0.0000 | -0.1194 | 0.5062 | 0.2276 | TRUE |
| Female: 62 to 64 years | 0.0000 | -0.3584 | 0.1626 | -0.1239 | TRUE |
| Female: 65 and 66 years | 0.0000 | -0.1784 | 0.4086 | 0.1105 | TRUE |
| Female: 67 to 69 years | 0.0000 | -0.2072 | 0.3396 | 0.1342 | TRUE |
| Female: 70 to 74 years | 0.0000 | -0.2815 | 0.2031 | -0.0507 | TRUE |
| Female: 75 to 79 years | 0.0000 | -0.2354 | 0.2365 | -0.0560 | TRUE |
| Female: 80 to 84 years | 0.0863 | -0.1139 | 0.4210 | 0.1324 | TRUE |
| Female: 85 years and over | 0.0377 | -0.1938 | 0.1619 | -0.0117 | TRUE |
| Median Age | 0.0000 | -0.0419 | 0.2316 | 0.0797 | TRUE |
| Total Households | 0.0000 | -0.2695 | 0.3955 | 0.0862 | TRUE |
| Average Household Size | 0.0000 | -0.0545 | 0.2095 | 0.0747 | TRUE |
| Total Housing Units | 0.0000 | -0.0947 | 0.9917 | 0.3907 | TRUE |
| Occupied Housing Units | 0.0000 | -0.4459 | 0.1310 | -0.1418 | TRUE |
| Vacant Housing Units | 0.1868 | -0.3502 | 0.0549 | -0.1469 | TRUE |
| Occupied Housing Units__1 | 0.0000 | -0.2624 | 0.2954 | 0.0121 | TRUE |
| Owned with a mortgage or a loan | 0.0000 | -0.1566 | 0.6600 | 0.2384 | TRUE |
| Owned free and clear | 0.0000 | -0.4927 | 0.1434 | -0.0713 | TRUE |
| Renter occupied | 0.0000 | -0.0892 | 0.5038 | 0.1460 | TRUE |

Table 14: Beta Coefficients for LASSO and BSLGPPR Models, continued.