Geographical Distribution of Crime in Minneapolis Neighborhoods: Dynamic Geographic Heat Map Analysis and Count Data Statistical Methods

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Abstract  
In the nowadays world, crime become an important social problem. There are many reasons to cause a crime, such as population, economic, education level, and public security. The aim of paper is to investigate the geographical distribution of crime in Minneapolis neighborhoods in the year 2011 to the year 2015. And concentrate on the two most important reasons cause a crime, which population and economic, investigate the relationship between the crime and the population, and the relationship between the crime and the economic. Using dynamic geographic heat map analysis, the paper investigates the spatial structure and distribution of the total crime and two main reasons cause the crime, which population and economic. Dynamic geographic heat map analysis allows us to discover some important geographical distribution and feature to let us investigate the relationship between the crime and the population, and the relationship between the crime and the economic. We employ three statistical regression methods to analysis the crime data such as Linear Regression Model, Poisson Regression Model, and Negative Binomial Regression Model.

Keywords: Geographic heat map, Crime Data, Count Regression Model

1. Introduction  
Crime is a form of blight on communities throughout the world because it is disruption to normal life and causes individuals and organizations to have lower confidence in their safety. Individuals or groups who commit crime often choose to do so on purpose, but it is often influenced by many external factors. Hence these factors become important in understanding how to mitigate crime. Crime is often used as an indicator of the overall health and vitality of a community. Specifically, there has been a great deal of research that are concerned with how factors of economic condition influence the occurrence of crime (Kelly, 2000; Linning, 2015; Sherman et al., 1989; see also Andresen & Linning, 2012; Andresen & Malleson, 2011; Bernasco & Block, 2011; Braga, Hureau, & Papachristos, 2011; Curman, Andresen, & Brantingham, 2015; Weisburd, Bruinsma, & Bernasco, 2009; Weisburd, Bushway, Lum, & Yang, 2004; Weisburd, Morris, & Groff, 2009; Linning et al., 2017). In order words, to better understand the impact of economic condition on the occurrence of crime in a community, this paper focuses on the cause of crime at the meso level, such as the neighborhood level rather than the micro or macro level, such as the individual or country level (Chiu & Madden, 1998; Cook, 2009; Levitt, 2001) because it gives a better idea of how to combat crime to local government officials than studies focusing on the country or individual level. Previous research on crime has contributed to finding out the determinants and

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deterrents of crime, but there are some gaps in addressing crime-related questions at a community level because the majority of studies concentrate on how to deal with crime in the whole societal or just individual level. Thus, this study examines causal factors at the neighborhood level that influence individual’s decision to supply crime. Especially, the relationships between income inequality and crime rates and between population density and crime rates are central points of examination.

Therefore, this paper aims to (1) investigate the geographical distribution of crime in Minneapolis neighborhoods in the year 2011 to the year 2015, (2) concentrate on the two most important and widespread causes of the crime, which is population density and poverty, and (3) investigate the impact of population density and poverty on crime.

Using dynamic geographic heat map analysis, we investigate the spatial structure and distribution of the crime and two most important determinants that cause the crime, which is population and poverty. Dynamic geographic heat map analysis allows us to discover some important geographical distributions and features of the crime to let us investigate the relationship between the crime and the population and the relationship between the crime and the poverty.

We also employ three statistical regression methods to analyze the data. There are Linear Regression Model, Poisson Regression Model, and Negative Binomial Regression Model. The linear regression mostly deals with a continuous response variable so that the case of the discrete response variable such as crime data may not be appropriate to use the traditional linear regression. So we want to show that the count data regression methods such as Poisson regression and negative binomial regression can be more suitable to analyze crime data rather than the traditional linear regression model in this paper.

In Section 2, we introduce Minneapolis neighborhoods crime by a dynamic geographic heat map analysis investigation, and Section 3 introduce count data statistical methods such as linear regression model, Poisson regression model and negative binomial regression model. In section 4, we show data analysis based on the three proposed statistical methods. The conclusion is followed.

2. Understanding the Cause of Crime
Understanding the occurrence of crime in a given area requires an examination of both the motivations of individuals to commit crime and the ability of society to prevent crime, and it is the deterrence theory that best describes the determinant of crime based on the conception of rational choice as a main element of engaging people in criminal acts.

There are a set of central points of this theoretical perspective, such as, (1) The human being is a rational actor who freely choose all behavior, both conforming and deviant, based on their rational calculations (2) Rational calculation involves a cost-benefit analysis, and (3) The human being choose all behavior that assure the maximization of individual pleasure and the minimization of the potential pain or punishment that will follow an act that is judged to be in violation of the social good (Beccaria, 1963; Bentham, 1948; Hobbes, 1962).

Hobbes (1962) ascertains that the human being is not either good or bad but commonly motivated to engage in deviant acts when criminal acts are frequently beneficial. So, achieving a maximum outcome of controlling criminal acts is always accompanied by a punishment that should be unpleasant, certain, and swift (Gibbs, 1968; Beccaria, 1963). In other words, crime is controlled by negative means in that a person has no desire to commit crime when the advantages are offset by the costs in committing criminal acts, and the costs should be assured by unpleasant, certain, and swift nature of punishment on a person who commit criminal acts (Gibbs, 1986). Thus, it is assumed that whether or not a person decides to engage in criminal wrongdoings is totally dependent on (1) how painful a punishment is inflicted on a person who commits criminal acts, (2) how definite a punishment is imposed on a person without considering any other alternatives, and (3) how expeditious a punishment is made for a person without delay (Beccaria, 1963; Tittle, 1969).
However, it is the society that is responsible for maintaining order and preserving the common good through swiftness, severity, and certainty of punishment that are the key elements in understanding a law's ability to control human behavior (Becker, 1968). In other words, society supplies criminal opportunities based on the costs of prevention, deterrence, and apprehension to reduce crime because factors embedded in a certain neighborhood influence the expected benefits to crime and affect the willingness of individuals to supply criminal offenses.

Cook (1986) also supports the role of neighborhood condition on motivating individuals to commit crime when explaining neighborhood as a market for criminal opportunities. Similar to Becker who emphasizes the socially created criminal opportunities, Cook (1986) explains the criminal opportunities supplied by certain community condition are those that have high payoff with little effort or risk of legal consequence. Thus, Cook (2009) suggests that society can find out ways to curtail the crime rate by reducing the payoff to the criminal, increasing the effort for the criminal, or increasing the risk of consequences for the criminal.

Rather than attempt to model the net benefit gained from crimes or probability-punishment profiles accepted by criminals, however, this study focuses on neighborhood characteristics that affect either the payoffs to crime or the probability of apprehension. And, the following section presents the review of previous studies that fills out this theoretical framework, while focusing on the impact of the poverty and population density of a region on crime.

3. Previous studies explaining the population density and poverty and their impact on crime

The impact of poverty on motivating individual to commit crime is widely discussed in previous studies. The social distress and personal dissatisfaction and frustration resulting from poverty seem more likely to influence an individual to commit crime than prospects of financial gain (Kelly, 2000; Brush, 2007; Block & Heineke, 1975). However, People resort to crime only if the loss of committing the crime are lower than the benefit gained from committing crime (Becker, 1968; Kelly, 2000, Chiu & Madden, 1998, Larsson, 2006). In other words, those living in poverty have a much greater inclination of committing crime because opportunity costs to punishment is usually lower than expected benefit from committing crime. Toby (1957) supports this assumption that people might resist criminal temptation if they knew that their conformity might be jeopardized by being engaged in crime. So, people with fewer stakes in conformity might have fewer reasons for resisting when faced with the opportunity for crime.

Social disorganization theory also posits the relationship poverty and crime. Shaw and McKay (1942) argued that communities with high poverty tend to lack the resources needed for building and maintaining effective community organization. In other words, concentrated poverty in the community seriously weakens the local tax base, which supports such community institutions as schools and recreational facilities. Additionally, the difficult circumstances of poverty mean that a significant portion of residents’ lives are focused on dealing with daily survival rather than resolving community matters, so asking them to spend time and energy organizing to help the community is to advise them to spend time in activity that fails to address their most immediate personal problems (Sampson & Groves, 1989). Furthermore, any neighborhood that is redeveloped through the process of gentrification also experiences the increase in crime because of the high level of social disorganization in the course of gentrification (Kreager et al., 2011).

Based on the findings of these previous studies, it is generally concluded that there is a positive relationship between poverty and crime, which means that the poverty in the individual level make a positive impact on individuals’ committing crime. However, the relationship between population density and crime is a difficult one to predict because of the differing effects of population density on the probability of apprehension and supply of criminal opportunities.

The population density as also been one of the major research topics for the cause of crime, and several theoretical perspectives showed a direct relationship between population density and crime, but
there is no consensus on the relationship population density and crime. Studies by Watts (1931), Calhoun (1962), and Craiglia et al. (2001) show that density has a positive impact on crime. Choldin (1978) suggests that overcrowding increases individuals’ anti-social behavior because of a higher concentration of potential targets and low probability of recognition of criminal wrongdoing (Glaeser & Sacerdote, 1999). This explanation is supported by routine activity theory (Cohen and Felson 1979), which emphasizes that crime is an ecological event that occurs within time and space. Cohen and Felson (1979) posit that crime events occur with several factors, such as the presence of motivated offenders and the presence of suitable targets. Cohen and Felson (1979) argue that a greater density of persons within environments indicates a larger number of potential targets, which could raise the crime rate irrespective of anomie effects, and greater density also potentially increases the number of motivated offenders in proximity to these suitable targets, who may commit more than one crime. Wirth (1938) who also suggests the positive association between population and crime posits that physical contacts increase within high-density environments because the high-density environment creates increased competition for urban space with resultant interpersonal friction and higher crime rates.

However, there is a theoretical explanation that focuses on the negative relationship density and crime caused by the frequent physical interaction. Studies like Jacops (1961) and Roncek (1981) suggest that in a residential neighborhood, population density discourages individuals to commit crime because individuals who interact frequently have more incentive to prevent crime from occurring in their neighborhood. In other words, individuals have a higher probability of being accountable for their actions when there are a great number people who are potential witnesses to crime in their neighborhoods that are densely populated. Thus, Roncek (1981) argues that there is a stronger negative relationship between population density and crime in the denser area.

Based on these previous studies, thus, it is suggested that population density and poverty is closely related with the crime rates in different geographical areas, and the following section will present an empirical data to support this assumption based on the dynamic geographical map analysis focusing on neighborhoods in Minneapolis so that it makes the findings of this study more relevant to many urban development policies that are centered on creating safe places and lively communities through reducing crime.

4. Crime in Minneapolis neighborhoods: a dynamic geographic heat map analysis investigation
Since long time, the crime is becoming one of the most important social problems. Many people are paying attention to this social problem, like sociologists and economists, and many websites are continuous to record, analysis and report the crime data, for example, FBI website have the crime data of all the states in the U.S., and every state has their own website to collect crime data.

For the Minneapolis, there are some state government websites like Minneapolismn.gov and some other websites like MINNPOST (see also Palazzolo et al., 2013). Minneapolismn.gov records the crime data, updates the data every month, and MINNPOST analyzes and reports the crime data every month. We chose the crime data from the Minneapolismn.gov and population data and income data from MINNESOTA COMPASS. The population data and income data give an average of 2011-2015 data, so for the crime data. We use dynamic geographic heat map to make these data like color shapes in the map to easily find out the differences in the crime rates of Minneapolis neighborhoods.

To make the dynamic geographic heat map, we need 4 processes: (1) create a shapes map; (2) set up the data table and name shapes; (3) create the legend and color scale; and (4) write the macros and run it (Yilmaz, 2017).

These three pictures show the total crime, population, and median household income in different Minneapolis neighborhoods. In these pictures, we can see every neighborhood have different color shape, and there are 6 different colors, and every color represents the different range of numbers from the range which is 0—1 to the range which is mean*1.25--mean*1.25*1.25. From Figure 1, we can see that areas in
middle have a darker color which represents an area with the high crime rate. And, this pattern is also comparable with the population and income data. As presented in figure 2 and 3, the population and income data also show that the middle part is darker than other areas in Minneapolis metropolitan area, and it indicates that neighborhoods in the middle of Minneapolis metropolitan area characterized as the high crime, overcrowdedness, and poverty.

On the other hand, these three maps show that the lower right part of Minneapolis metropolitan area is depicted in the lighter color which means being less-crowded, lower crime rate, and higher income than other parts of Minneapolis. This analysis based on a dynamic geographic heat map is also proved by the following correlation table.

### Table 1. Correlation Table

<table>
<thead>
<tr>
<th></th>
<th>Total Crime</th>
<th>Population</th>
<th>Median Household Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Crime</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>0.526140855</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Median Household Income</td>
<td>-0.279180495</td>
<td>-0.288255548</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Authors’ Statistical Analysis using SPSS

It shows that the total crime and population have about 0.526 correlation which is positive, so the total crime and population have positive relationship meaning that when population increase, the total crime will increase. It also shows the total crime and median household income have about -0.279 correlation which is negative, so the total crime and median household income have negative relationship meaning that when median household income increase, the total crime will decrease.

### 5. Statistical Methods

#### 5.1. Poisson Regression

Poisson regression is similar to regular multiple regression except that the dependent (Y) variable is an observed count that follows the Poisson distribution. Thus, the possible values of Y are the nonnegative integers: 0, 1, 2, 3, and so on. It is assumed that large counts are rare. Hence, Poisson regression is similar to logistic regression, which also has a discrete response variable. However, the response is not limited to specific values as it is in logistic regression.

One example of an appropriate application of Poisson regression is a study of how the colony counts of bacteria are related to various environmental conditions and dilutions. Another example is the number of failures for a certain machine at various operating conditions. Still another example is vital statistics concerning infant mortality or cancer incidence among groups with different demographics. Most books on regression analysis briefly discuss Poisson regression. We are aware of only one book that is completely dedicated to the discussion of the topic. This is the book by Cameron and Trivedi (2005). Most of the methods presented here were obtained from their book.

This program computes Poisson regression on both numeric and categorical variables. It reports on the regression equation as well as the goodness of fit, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform a subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values.

The Poisson distribution models the probability of y events (i.e. failure, death, or existence) with the formula:

\[
\Pr(y = y | \mu) = \frac{e^{-\mu} \mu^y}{y!} (y = 0, 1, 2, \ldots)
\]

Notice that the Poisson distribution is specified with a single parameter \( \mu \).
Figure 1. Crime Data of Minneapolis Neighborhoods Based on Dynamic Geographic Heat Map Analysis

Source: MINNPOST & MINNESOTA COMPASS Data, 2011-2015
Figure 2. Population Data of Minneapolis Neighborhoods Based on Dynamic Geographic Heat Map Analysis

Source: MINNPOST & MINNESOTA COMPASS Data, 2011-2015
Figure 3. Income Data of Minneapolis Neighborhoods Based on Dynamic Geographic Heat Map Analysis

Source: MINNPOST & MINNESOTA COMPASS Data, 2011-2015

This is the mean incidence rate of a rare event per unit of exposure. Exposure may be time, space, distance, area, volume, or population size. Because exposure is often a period of time, we use the symbol \( t \) to represent the exposure. When no exposure value is given, it is assumed to be one.

The parameter \( \mu \) may be interpreted as the risk of a new occurrence of the event during a specified exposure period, \( t \). The probability of \( y \) events is then given by
The Poisson distribution has the property that its mean and variance are equal. In Poisson regression, we suppose that the Poisson incidence rate $\mu$ is determined by a set of $k$ regressor variables (the X’s). The expression relating these quantities is

$$\mu = t \exp(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)$$

Note that often, $X_1 = 1$ and $\beta_1$ is called the intercept. The regression coefficients $\beta_1, \beta_2, \cdots, \beta_k$ are unknown parameters that are estimated from a set of data. Their estimates are labeled $\hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_k$.

Using this notation, the fundamental Poisson regression model for an observation $I$ is written as

$$\Pr(y_i | \mu_t, t_I) = \frac{e^{-\mu_t I} (\mu_t I)^y_i}{y_i !}$$

Where

$$\mu_t = t_I \mu (X | \beta) = t_I \exp(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)$$

That is, for a given set of values of the regressor variables, the outcome follows the

5.2. Negative Binomial Regression

Negative binomial regression is similar to regular multiple regression except that the dependent (Y) variable is an observed count that follows the negative binomial distribution. Thus, the possible values of Y are the nonnegative integers: 0, 1, 2, 3, and so on.

Negative binomial regression is a generalization of Poisson regression which loosens the restrictive assumption that the variance is equal to the mean made by the Poisson model. The traditional negative binomial regression model, commonly known as NB2, is based on the Poisson-gamma mixture distribution. This formulation is popular because it allows the modelling of Poisson heterogeneity using a gamma distribution.

Some books on regression analysis briefly discuss Poisson and/or negative binomial regression. We are aware of only a few books that are completely dedicated to the discussion of count regression (Poisson and negative binomial regression). This program computes negative binomial regression on both numeric and categorical variables. It reports on the regression equation as well as the goodness of fit, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform a subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values.

The Poisson distribution may be generalized by including a gamma noise variable which has a mean of 1 and a scale parameter of $\omega$. The Poisson-gamma mixture (negative binomial) distribution that results is

$$\Pr(y_i | \mu_t, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1) \Gamma(\alpha^{-1})} \left( \frac{\alpha^{-1}}{\alpha^{-1} + \mu_t} \right)^{\alpha^{-1}} \left( \frac{\mu_t}{\alpha^{-1} + \mu_t} \right)^{y_i}$$

where

$$\mu_t = t_I \mu$$

$$\alpha = \frac{1}{\omega}$$

The parameter $\mu$ is the mean incidence rate of $y$ per unit of exposure. Exposure may be time, space, distance, area, volume, or population size. Because exposure is often a period of time, we use the symbol $t_I$ to represent the exposure for a particular observation. When no exposure given, it is assumed to be one. The parameter $\mu$ may be interpreted as the risk of a new occurrence of the event during a specified exposure period, $t$. 

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The results below make use of the following relationship derived from the definition of the gamma function:

\[
\ln \left( \frac{\Gamma(y + \alpha^{-1})}{\Gamma(\mu)} \right) = \sum_{j=0}^{y-1} \ln(j + \alpha^{-1})
\]

In negative binomial regression, the mean of \( y \) is determined by the exposure time \( t \) and a set of \( k \) regressor variables (the \( x \)'s). The expression relating these quantities is

\[
\mu_i = \exp \left( \ln(x_i) + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \right)
\]

Often, \( x_1 = 1 \), in which case \( \beta_1 \) is called the interpret. The regression coefficients \( \beta_1, \beta_2, \ldots, \beta_k \) are unknown parameters that are estimated from a set of data. Their estimates are symbolized as \( \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_k \).

Using this notation, the fundamental negative binomial regression model for an observation \( i \) is written as

\[
\Pr(r = y_i | \mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\mu_i) \Gamma(y_i + 1)} \left( \frac{1}{1 + \alpha \mu_i} \right)^{y_i} \left( \frac{\alpha \mu_i}{1 + \alpha \mu_i} \right)^{\mu_i}
\]

5.3. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

The Akaike Information Criterion (AIC) is as one of the most commonly used fit statistics. Let \( \mathcal{L} \) be the maximum value of the likelihood function for the model. It has two formulations:

\[
AIC(1) = -2[\mathcal{L} - k]
\]

and

\[
AIC(n) = \frac{2}{n} [\mathcal{L} - k]
\]

Note that \( k \) is the number of predictors including the intercept. AIC(1) is usually output by statistical software applications.

The Bayesian Information Criterion (BIC) is another common fit statistic. It has three formulations:

\[
BIC(R) = D - (df) \ln(n)
\]

\[
BIC(L) = -2\mathcal{L} + kn \ln(n)
\]

\[
BIC(Q) = \frac{2}{n} [\mathcal{L} - k \ln(k)]
\]

Note that \( df \) is the residual degrees of freedom.

Note that BIC(L) is given as SC in SAS and simply BIC in other software.

6. Data Analysis

We use three models to analyze the data, and there are Linear Regression Model, Poisson Regression Model, and Negative Binomial Regression Model.

First is Linear Regression Model. Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable. The Linear Regression Model shows this table:
Table 2. Linear Regression Model Coefficients Table

| Coefficients: | Estimate | Std. Error | t value | Pr(>|t|) |
|---------------|----------|------------|---------|----------|
| (Intercept)   | 79.8086365 | 106.020085 | 0.696   | 0.488    |
| Population    | 0.061731   | 0.012302   | 5.018   | 2.98E-06 |
| Median.Household.Income | -0.001147 | 0.001147 | -1.436 | 0.155    |

Source: Authors’ Statistical Analysis using SPSS

As we can see from the table, the estimate of population is 0.062 which means that the relationship between the total crime and the population is positive, and the p-value of population is 2.98e-06 that shows this relationship is very significant. But, the p-value of median household income is 0.155 which is close to the 0.1, so it is not significant and cannot use the estimate of median household income.

Second is Poisson Regression Model. Poisson regression is a generalized linear model form of regression analysis used to model count data and contingency tables. Poisson regression assumes the response variable Y has a Poisson distribution and assumes the logarithm of its expected value can be modeled by a linear combination of unknown parameters. The Poisson regression model is sometimes known as a log-linear model, especially when used to model contingency tables. The Poisson Regression Model is shown in this table:

Table 3. Poisson Regression Model Coefficients Table

| Coefficients: | Estimate | Std. Error | z value | Pr(>|z|) |
|---------------|----------|------------|---------|----------|
| (Intercept)   | 5.05E+00 | 2.50E-02   | 202.05  | <2e-16   |
| Population    | 1.73E-04 | 2.24E-06   | 77.22   | <2e-16   |
| Median.Household.Income | -7.23E-06 | 2.97E-07 | -24.35 | <2e-16   |

Source: Authors’ Statistical Analysis using SPSS

As shown in Table 3, the estimate of population is 1.73e-04 meaning that the relationship between the total crime and the population is positive, and the p-value of population is <2e-16, so this relationship is very significant. Furthermore, the estimate of median household income is -7.23e-06 which means that the relationship between the total crime and the median household income is negative, and the p-value of median household income is <2e-16 that shows this relationship is very significant.

Third one is Negative Binomial Regression Model. Negative binomial regression is a popular generalization of Poisson regression because it loosens the highly restrictive assumption that the variance is equal to the mean made by the Poisson model. The traditional negative binomial regression model, commonly known as NB2, is based on the Poisson-gamma mixture distribution. This model is popular because it models the Poisson heterogeneity with a gamma distribution. The Negative Binomial Regression Model shows this table:
Table 4. Negative Binomial Regression Model Coefficients Table

| Coefficients:          | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------------|----------|------------|---------|---------|
| (Intercept)            | 4.79E-01 | 2.15E-01   | 22.17   | <2e-16  |
| Population             | 2.34E-04 | 2.49E-05   | 9.384   | <2e-16  |
| Median.Household.Income| -8.31E-06| 2.33E-06   | -3.553  | 0.000367|

Source: Authors’ Statistical Analysis using SPSS

We can see from Table 4, the estimate of population is 2.34e-04, it means that the relationship between the total crime and the population is positive. And, the p-value of population is <2e-16, which means that this relationship is very significant. Furthermore, the estimate of median household income is -8.31e-06, meaning that the relationship between the total crime and the median household income is negative, and the p-value of median household income is 0.000367, which is close to the 0, so it shows this relationship is very significant.

Finally, we make the AIC and BIC table of this three models shown in the following:

Table 5. AIC and BIC Table

<table>
<thead>
<tr>
<th>Model</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Regression Model</td>
<td>1196.503</td>
<td>1206.274</td>
</tr>
<tr>
<td>Poisson Regression Model</td>
<td>10699.53</td>
<td>10706.86</td>
</tr>
<tr>
<td>Negative Binomial Regression Model</td>
<td>1041.412</td>
<td>1051.183</td>
</tr>
</tbody>
</table>

Source: Authors’ Statistical Analysis using SPSS

In this table, the AIC and BIC of the Negative Binomial Regression Model is smaller than Linear Regression Model and Poisson Regression Model, so we can say that the negative binomial regression model is the best model for this crime data among other three regression models in this paper.

7. Conclusions and Policy Suggestions
In the dynamic geographic heat map, we can conclude that if neighborhoods were more densely populated, they would have more crime, and if neighborhoods had the income level that is higher than average, there would be less crimes in those neighborhoods. This result is further supported by several statistical findings. In Table 1, the correlation of the total crime and the population is 0.526, meaning that the total crime and the population is positive relationship, and the correlation of the total crime and the median household income is -0.279, which means that the total crime and the median household income is negative relationship.

In Table 2, we can see that the estimate of population is 0.062, meaning that the relationship between the total crime and the population is positive. In Table 3, the estimate of population is 1.73e-04, which means that the relationship between the total crime and the population is positive, and the estimate of median household income is -7.23e-06, meaning that the relationship between the total crime and the median household income is negative. In Table 4, we can see that the estimate of population is 2.34e-04, which means that the relationship between the total crime and the population is positive, and the estimate of median household income is -8.31e-06, meaning the relationship between the total crime and the median household income is negative. Based on the above three statistical methods, thus, we can conclude that the relationship between the total crime and the population is positive, and the relationship between the total crime and the median household income is negative. So, we confirmed that the research shown in this paper based on employing the count data regression models support the hypothesis that the
more densely populated neighborhoods are, the more crimes they have, and the less the income level they have, the more crimes they experience.

The results and inferences of this study can be used as possible applications for urban planning. It is true that statistical results cannot tell us everything, but they can point us in the right direction to identify policies that reduce crime and improve urban life. For example, we can think about the urban planning through making housing and development laws that can effectively deal with population density impacting on residents’ behavioral pattern. According to Paulsen (2013), many policy planners see the importance of building a physical environment to successfully combat crime in the area of dense population.

One of the ideas to combat crime under the circumstance in that the area becomes overcrowded is centered on the creation of “defensible space” that gives residents a sense of ownership over their neighborhoods through the process of private partition, building physical fences or separating high-traffic major roads from residential access avenues by creating cul-de-sac in street design, so it makes easier for residents to surveil their own private property (Newman, 1996). This environmental design is based on the policy that focuses on the importance of decreasing interaction among the residents in neighborhoods. Rather than the separation and division of space, Paulsen (2013) suggests more connectivity among streets and neighborhoods as ways to increase interaction, such as supporting the creation of cul-de-sacs as a means of assigning ownership. This policy suggestion is also supported by Jacobs who suggests that when the area becomes densely populated, crime can be controlled by the environmental design that encourage walking and social interaction. These previous studies added with the findings of this study can contribute to policymakers’ finding out ways of combatting crime using neighborhood-oriented policies related with urban development planning.

8. Limitations and Considerations for Future Study
There are a number of limitations in this study. First of all, the limited number of causal factors in this study prevents researchers from having a more comprehensive understanding of why there is the relationship between the socioeconomic standing of a neighborhood and the crime rate. In other words, there are many other important variables that measure the socioeconomic condition of a neighborhood besides poverty measured by the income level of neighborhoods on the crime rate in different neighborhoods, and those variables are also closely related with the crime rates in the neighborhood level, such as housing value (Kelling& Wilson, 1982), housing vacancy rate (Ellen, Lacoe, and Sharygin, 2013), unemployment rate (Levitt, 2001; Toby, 1957), high school graduation rate (Cook, 2009), and female-headed household rate (Glaeser&Sacerdote, 1999). In addition, it is also important to include a variable of racial diversity that is highly associated with the regional difference in crime rates. Krivo and Peterson (2009) suggest that a neighborhood with the high racial/ethnic diversity might have the low level of interaction among the members of a neighborhood creating a higher level of social disconnect and a higher expected return to crime. In light of these findings in the literature, it is possible that in addition to income these additional variables can be used as independent variables on crime rates in a neighborhood or act as a mediating variable in the relationship between poverty and crime in the regression model.

In addition, it is necessary to think about the interaction effect between population density and poverty on crime. As suggested by Popkin et al. (2012), neighborhoods with density and poverty are more likely to be concerned about crime because residents in poor neighborhoods are less likely to report crime for number of reasons, such as the fear of retaliation, the fear of having their own criminal activities discovered, and the fear of having the interference with earnings and employment activities.

Moreover, expanding the study to more cities would allow closer examinations of patterns across different types of cities. Differences in urban development patterns over time and differences between older and newercities could be different.
Lastly, using mixed method can be useful to have a better understanding of the condition of the neighborhoods because the quantitative data do not tell us everything about how residents live in a neighborhood and how a neighborhood is structured. Aspects of urban life are highly intertwined, and it can be difficult to differentiate the impact of certain factors just by looking at the findings bya regression model. Thus, we must always keep in mind the limits of statistical models and consider broader perspectives based in the realities and peculiarities of individuals lives.

References


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