Toward the Onset of Space-Crime Diffusion: Spatial Patterns and their Interactions with Criminogenic Factors

Zhihang Dong*
Department of Sociology
University of Washington
Seattle, 98115
zdong@uw.edu

Abstract

This paper discusses the spatial patterns of crimes differentiated by the type of crime, the geographical unit of analysis and the selection of covariates. Findings suggest the "spillover" effects of crime are more salient for property-related crimes, crimes for the sole purpose of physical or material harm have weaker diffusion, especially in larger geographical unit of analysis. Crimes that demonstrate the strongest power of diffusion are those motivated for resources one feel entitled but is deprived of, whereas crimes that demonstrate weaker diffusion activities are those located within a strong regional subculture. These findings shed light on the concepts of institutional anomie and relative deprivation in criminology, but also suggest future scholars to consider more carefully about the spatial regime to tell "stories" about the spatial diffusion of crimes in areas they observe.

1 Introduction

Spatial analysis is one of more rapidly-developing areas with applications in inequality, health, criminology and many more fields (Morenoff, Sampson and Raudenbush 2001; Taylor 2015; Tickamyer 2000). According to Anselin et al. (2000), social scientists have invested an increasing amount of effort in the advancement of knowledge regarding the spatial diffusion of deviance. In one of the applied paper about the spatial processes of crime, Baller et al. (2001) investigated the spatial processes on county-level homicide rates, and found homicide is clustered in space. Studies have also concerned other types of violence using different levels of analysis (Deane et al. 1998; Messner et al. 1999). The science of spatial methodology has contributed to the empirical studies of deviance in general by proposing a new state of mind, and subsequently explaining why neighborhoods with similar attributes otherwise fare differently in crime rates.

Findings from the previous studies have encouraged an increasing number of scholars using their spatial analysis toolbox in the sociological context. Beyond the continuous effort of interpreting spatial effects on homicide (Andresen and Malleson 2015; Vilalta and Muggah 2014; Nivette 2012), scholars tested the theories and hypotheses with spatial perspective in many other contexts of criminal violence, such as robbery (Harper, Khey and Nolan 2013; Ceccato and Oberwittler 2008; Deane et al. 2008), rape (Socia, 2013; Lundrigan, Czarnomski and Wilson 2010), and assault (Bones and Hope 2015; Livingston 2008; Rotton and Cohn 2004). In addition, some studies expand their interests by including non-violent crimes: Asgary et al. (2013) used pattern analysis in ESDA to study burglary in residential areas; Breetzke (2012) studied the effect of altitude and slope on burglary

*This is a working paper still in development. Please do not cite, use, reproduce any part of this paper without the explicitly approval of the author.

patterns; Homel, Chaseling and Townsley (2000) applied the spatial-temporal pattern analysis in repeated burglary victimization.

Ideally, these studies should have provided substantial knowledge for scholars and policymakers seeking to compare spatial effects across various types of crime. However, with different data sources and analytical strategies, studies with spatial analysis are more complicated to compare-and-contrast. For example, it is difficult to use studies using county as the unit of analysis to compare to studies using census tracts as the unit of analysis: the ignorance of different reference systems may create ecological bias, which ultimately leads to the wrong inference. The described difficulty implies that the simple contrast of studies may assume major inconsistency of analytical framework, so that the conclusions so drawn are likely invalid. The knowledge of how the diffusion processes (see Baller et al. 2001) of common types of crimes differ may be helpful in increasing the effectiveness of crime-prevention tactics. Specifically, it is widely perceived by the audience of crime prevention studies that some types of crime (such as robbery) are much more diffusive than the others (such as murder). For example, the city of Seattle only observed only few dangerous spots (where murders and aggravated assaults frequently happen), but the entire city suffers from the epidemic of burglary, making it one of the safest major city in America in terms of violent crime rate but one of the most property-dangerous city in burglary, theft and auto theft in the year of 2015. Previous research has attempted but fully explained the discrepancies of different types of deviance in diffusion power, which makes the pursuit of this topic helpful in sociologically understand the cause of these differences in the spatial mechanism.

Hence, the current paper applies the spatial techniques in the context of aggregate crime data using a fixed scheme of Seattle census tract as the unit of reference. The analytical procedures are to compare the mechanism of spatial diffusion over six Uniform Crime Reporting Part I (UCR I) offenses. Methodologically, I am going to first examine the clustering of the different types of crimes, and construct smoothing models to map the spatial variations. In consideration of the spatial effects (if spatial variation exists), I then provide the spatial regression outcomes. Finally, the results in the census tract level is to be compared with the similar analysis taken in place of the county level as the unit of reference, in the state of Texas. By briefly compare and contrast the difference of findings at various levels, I intend to elaborate the differential spatial patterns of crime performed under different observational units and categorical definitions. At the end, I intend to explain how spatial patterns can tell stories about the different types of crimes in the local level, and the policy implication behind the spatial inference findings.

2 Data Sources

The census tract shapefiles and population information are dowloaded online from the Office of Planning Community Development, the American Fact Finder from the American Community Survey (ACS), 5-Year Estimate for 2010-2014. Finally, the crime data are downloaded online from the Seattle Police Department 911 Incident Response of the Public Safety Section of the Seattle Open Data Center website.

The data to be downloaded from the crime data contain murder, robbery, burglary, theft, assault, and property damage crimes reported by the 911 Incident Response data from 2009 to Feburary 2017. The demographic data contain the ACS 5-year estimate of poverty rates, population without high school degrees aged over 25, and the racial heterogeneity measurement (measured by the minority population divided by the overall population). For the crime data, each type of crime is representated by unstandardized (raw) counts, and the *standardized mortality ratio* (SMR) of crime, in which mortality is equivalent to an incidence of crime. The SMR is calculated by:

$$\text{SMR}_i^j = \frac{Y_i^j}{\sum_j Y_i^j K_j / \sum K} = \frac{Y_i^j}{E_i^j} \tag{1}$$

where Y_i^j is the observed crime counts for census tract j of the crime type i. K is the population for census tract j. E is the expected crime counts, which is the product of total number of crime counts for crime i divided by the total population of the Seattle $\sum K$ multiplies with the census tract population K_j.

Full descriptions and standalone files of the data, codes, compilers, supplements and plot gallary can be found from my GitHub page.

`https://github.com/biggyd/Seattle-Crime`

3 Methods

3.1 Clustering of Crimes over the Space

Figure 1 is the histogram of total crime rates in Seattle. The subset of crime rates by type is similar in terms of distribution being right-skewed. Studying the distribution of crimes across the space starts from the fundamental assumption that the distribution is not uniform. Therefore, the first step of this study is to examine the clustering of different types of crime. The spatial clustering exists if there is significant local spatial variation in residual risk. Figure 17 below is a map of crime rates for the six types of crime (homicide, burglary, robbery, theft, property damage (including arson, which is officially one of the Type I crime in UCR) and assault). It is not hard to visually perceive that census tracts in the central areas have the highest crime rates, the crime rate is very high of the surrounding areas, but the crime rates are generally higher in the ”south” than in the ”north”.This indicates some evidence of *overdispersion*, which means the distribution of crime over the space is not following the Poisson model or negative binomial model assumptions.

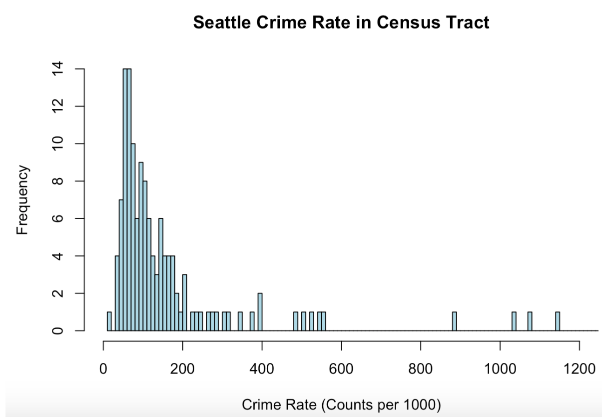

Figure 1: Histogram of Crime Rates

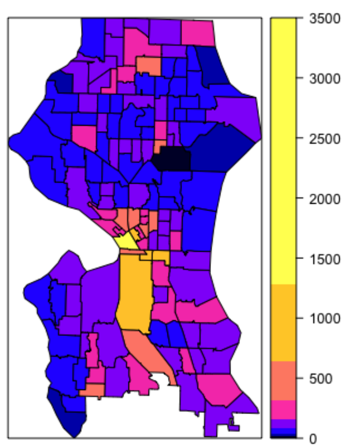

Figure 2: Maps of Crime Rates for full crimes in Seattle

To assess the overdispersion, I conduct a Monte Carlo test to examine the significance of overdispersion, using the quasipoisson models. The dispersion parameter κ is 5.763, which demonstrates significant overdispersion. This finding leads us to explore the spatial dependence of different types of crimes. First, I calculate the clustering statistic for different types of crime. The two popular ones are the Moran's I and Geary's C. Moran's I statistics (Moran, 1948) is given by:

$$I = \frac{1}{S^2} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(Z_i - \overline{Z})(Z_j - \overline{Z})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{2}$$

when I will be close to zero if there is no spatial dependence. Geary's c is similar when c will be close to zero if there is no spatial dependence, with one major difference: the c will be close to 1 if there is no spatial autocorrelation.

$$c = \frac{1}{S^2} \frac{\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(Z_i - Z_j)^2}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{3}$$

It is obvious here that Geary's c deals with the biases caused by the outliers of the skewed distribution because its interaction is the deviations in intensity of each observation against another, which is not heavily influenced as the calculation of cross-product as the Moran's I. Using the weighting scheme standardize rows by the number of neighbors such that the sum of each row is unity. We present the results of spatial autocorrelation test in the table below.

Type of Crime	Moran's I	Geary's c
Robbery	0.2750^{***}	0.7207^{**}
Burglary	0.3175^{***}	0.6632^{***}
Theft	0.1303^{***}	0.8166^{*}
Property Damage	0.1585^{***}	0.8958^{-}
Homicide	0.2729^{***}	0.7208^{***}
Assault	0.3495^{***}	0.6633^{***}

Both methods confirm all types of crime but the property damage. The spatial autocorrelation for homicide, robbery, burglary, theft and assault is very obvious. The disagreement of the two methods on property damage is trivial, because the autocorrelation for both methods are still minimally significant at least. To detect local influence, we may plot the lagged response (which is residuals) versus the response and examine if there are areas with too large of an influence. Figure 17 in the Appendix is the map of Seattle with codes we use in this paper. Figure 3 is the LISA plot showing areas with high local influence.

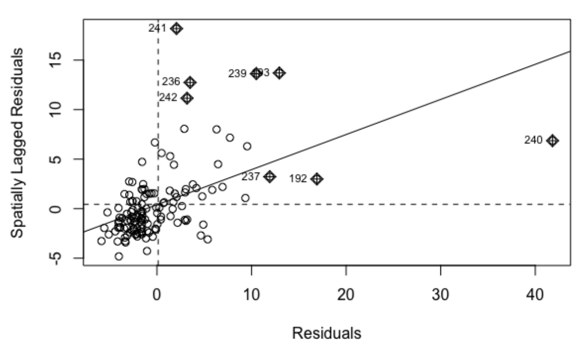

Figure 3: LISA plots on local influence

There are a few areas with large local influence. Here, we plot the map again after calculating the locaal contributions (as z score) for the quasipoisson modeling accounting for the spatial information (easting and northing). Figure 4 is the example for the robbery case. As same as Figure 18 (in

Appendix) case for homicide, the other types of crimes hold the similar outcome. There seems to be Therefore, we are able to conclude that there are spatial autocorrelation at the census tract level across the major type of crimes, and the "local hotspots" are similar across different types of crimes. However, the identification of spatial autocorrelation does not identify the variability of underlying risk. For this purpose, we should be considering the mapping and smoothing procedures.

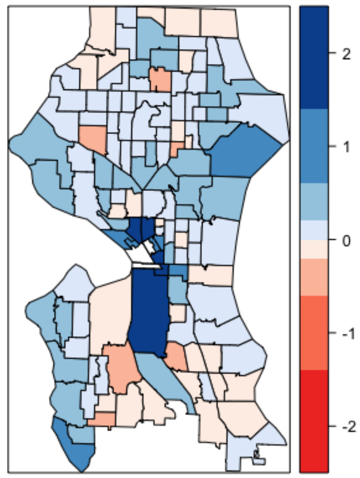

Figure 4: Local Contribution

3.2 Mapping and Smoothing

Crimes (especially homicide) usually have very small expected values in unit of analysis as small as census tract. Given that:

$$\mathrm{var}(\mathrm{SMR}_i) = \frac{\mathrm{SMR}_i}{E_i} \tag{4}$$

when the expected number of cases, the variability of the SMR is high, and contribute to the instabilities, which leads to the smoothing of SMRs using hierarchical or random effects. In this study, I compare the previously used basic Poisson model with the random effects models using or not using the spatial smoothing, with or without covariates to get the best outcome of the smoothing.

3.3 Poisson-Gamma Smoothing model

The SMR maps on spatial diffusion effects of different crimes are provided in appendix. One of the simpler model is the Poisson-Gamma two-stage model. In this model, the relative risk is constant across all areas, which is the β_0.

$$Y_i|\beta_0, \delta_i \sim_{iid} \mathrm{Poisson}(E_i \exp(\beta_0)\delta_i) \tag{5}$$

When Y_i = 0, we obtain an SMR of 0, and a standard error of zero. Since this is unacceptable, we adjust the E by adding 0.5 to each zero case. The assessment of gamma assumption is to plot the ordered observed residual relative risks against the expected relative risk from the gamma distribution. Therefore, the appropriateness of modeling is determined by how closely aligned the data points to the straight line. From Figure 5, we are able to conclude the gamma assumptions are held well.

We then plot the standard plot of SMRs versus standard errors (SE) of SMRs against the empirical smoothed Bayes estimates versus the respective SE. Figure 6 shows pretty obvious that the shrinkage of Bayes estimates and the smoothed SE. This is further demonstrated in Figure 7.

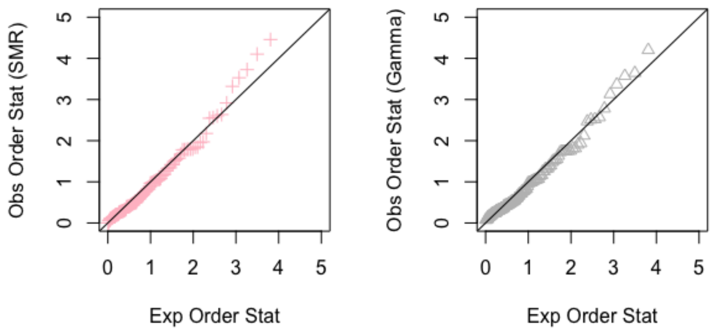

Figure 5: Assessment of gamma assumption

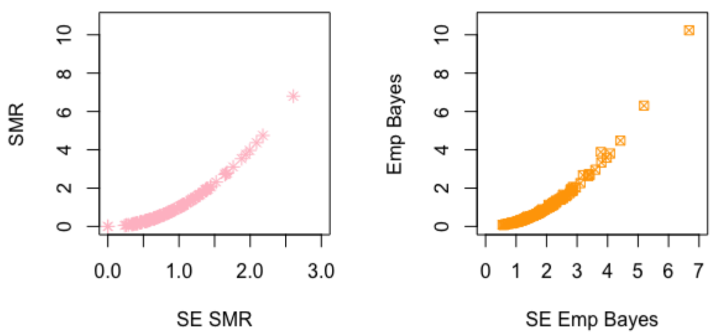

Figure 6: Standard vs. Bayes

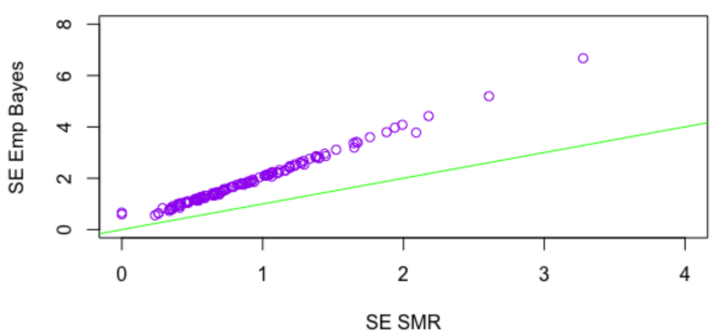

Figure 7: SE of SMR versus SE of Empirical Bayes

To get the uncertainity estimates for the Empirical Bayes estimators, we calculate the 2.5% and 97.5% points of the gamma posteriors of the relative risks. Figure 8 shows that Empirical Bayes methods generally have lower interval width, which means a smaller uncertainty.

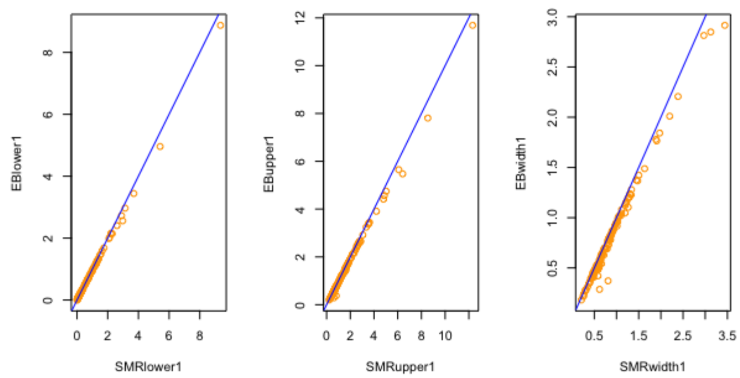

Figure 8: Interval Width for Gamma assumptions

We now fit the gamma smoothing model with covariate of poverty. For the economy of the space, I am only using this model with one pair of attempt: robbery with the covariate of poverty rate. Figure 9 demonstrates how SMR increase with the poverty rate. Because the variance of the gamma model Ga(α, α) is $1/\alpha$. The variance of the random effects is decreased from 0.913 to 0.496. This means some of the variability are explained by the covariate. Using the same logic, we process this process to other demographic variables, the demographic covariate that successfully reduced the variability is the poverty rate, percentage of population without high school degree age over 25, and the racial heterogeneity. Figure 19 also compared the model without (Model 1) and with (Model 2) covariates. Gamma smoothing models with the covariate tends to estimate a higher relative risk.

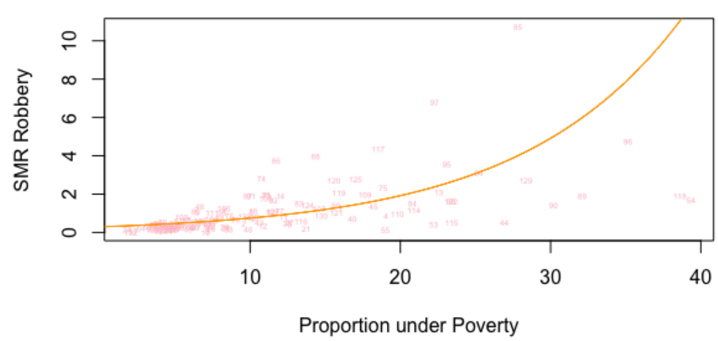

Figure 9: Gamma Smoothing model with Covariate

3.4 Poisson Lognormal Model

The Poisson-Gamma model is computationally easy, but unable to account for residual spatial dependence. To take the spatial dependence into the plan, we now turn to the Poisson-lognormal non-spatial random effect model, which is is given by:

$$\begin{aligned} Y_i|\beta_0, \epsilon_i &\sim_{ind} \text{Poisson}(E_i \mathrm{e}^{\beta_0} \mathrm{e}^{\epsilon_i}), \\ \epsilon_i|\sigma_\epsilon^2 &\sim_{iid} N(0, \sigma_\epsilon^2) \end{aligned}$$

where ϵ_i are area-specific random effects that capture the residual or unexplained (log) relative risk of disease in area i, $i = 1, ..., n$. For Poisson-Lognormal, a prior must be specified, we specify the 5% and 95% points of the relative risk associated with β as 1 and 5. The specification of the prior for the precision is $\tau_\epsilon = \sigma_\epsilon^{-2} \sim \text{Ga}(0.5, 0.0005)$. The full posterior, which is an $(n+2)$-dimensional distribution is specified below:

$$p(\beta_0, \tau_\epsilon, \epsilon_1, \ldots, \epsilon_n | y) = \frac{\prod_{i=1}^{n} \Pr(Y_i|\beta_0, \epsilon_i) p(\epsilon_i|\tau_\epsilon) p(\beta_0) p(\tau_\epsilon)}{\Pr(y)}. \tag{6}$$

We now turn to compare the Poisson-lognormal model and the Poisson-gamma model. The Lognormal model without covariate seems to have similar estimates compared to the Gamma model, except it seems to overestimate relative risk than Gamma model when RR is higher, but underestimate a bit than Gamma model when RR is lower.

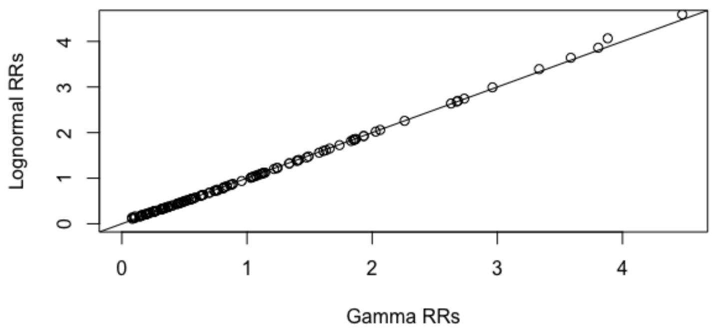

Figure 10: Comparison Lognormal vs. Gamma

The difference between Lognormal model and gamma model can be further illustrated in Figure 11 and 12. When there is no covariate considered, the difference between lognormal model and gamma model in this estimate is trivial.

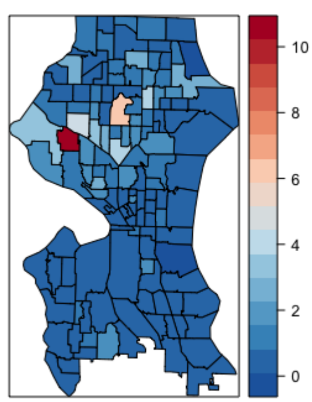

Figure 11: Gamma Model Covariate RR Estimate

Lognormal model also did a good job in narrowing the interval widths for uncertainty. Figure 13 showed the comparison of lognormal model with the regular Poisson model. As it is shown, the interval width for Poisson-Lognormal model is much smaller.

Using the example again from the poverty-robbery pair, The posterior mean for the intercept is $E[\beta_0|y] = -1.378$.

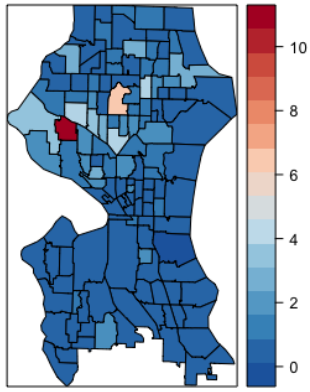

Figure 12: Lognormal Model Covariate RR Estimate

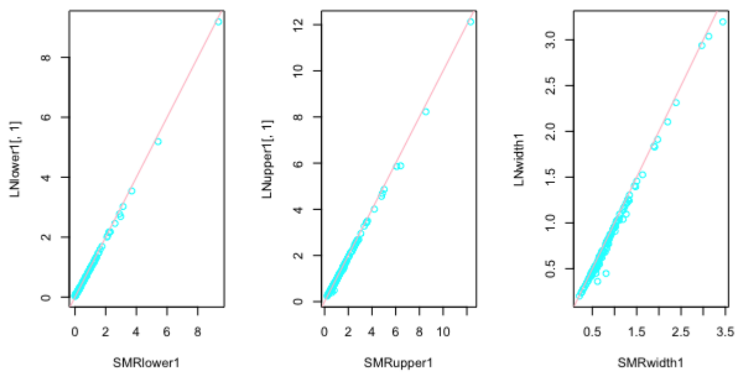

Figure 13: Interval width of Lognormal model

The posterior median for the relative risk associated with a 1 unit increase in X is $\text{median}(\exp(\beta_1)|y) = \exp(0.085) = 1.09$.

Similarly a 95% credible interval for the relative risk $\exp(\beta_1)$ is

$$[\ \exp(0.0692), \exp(0.1026)\ ] = [\ 1.072, 1.108\ ].$$

Examination of such intervals made us have strong evidence that the relative risk of robbery associated with poverty is significant.

3.5 Poisson-Lognormal with Covariate and Spatial Effects

Finally, we add the spatial (ICAR) random effects to the smoothing model. We calculate the estimates of residual relative risk (posterior medians), of the non-spatial e^{ϵ_i} and the spatial contributions e^{S_i}. The ICAR Random effects Poisson-Lognormal model with covariate is: $Y_i|\theta_i \sim \text{Poisson}(E_i\theta_i)$ with

$$\log\theta_i = \beta_0 + \beta_1 x_i + \epsilon_i + S_i.$$

The model made a significant difference compared to the non-spatial models. Figure 14 and Figure **??** demonstrated how different the two was.

When accounting the same poverty-robbery model with the spatial effects, the posterior mean estimate of β_1 associated with poverty goes from 0.307 to 0.232 when moving from the non-spatial to

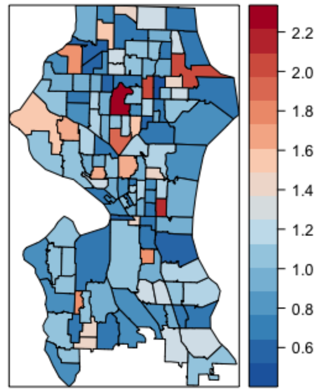

Figure 14: Nonspatial model

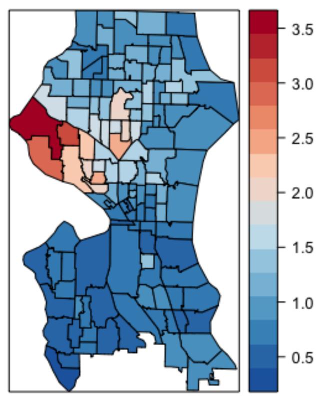

Figure 15: Spatial ICAR model

spatial model. This means the robbery crimes are very much confounding by the location. Calculating the proportion of variation by spatial effects, the spatial effects account for 57% of the variation, which is very significant. Similarly, we run the spatial effects in other crime-demographic pairs, the spatial effects account for 30 - 69% of the variation. This means the spatial ICAR random effects Poisson-Lognormal model is desired. Figure 16 demonstrated the shrink of interval width under this model, which also proved its significance. As a result, we will turn on to the spatial regression to test the spatial effects on models of different types of crimes.

4 Results

To formally analyze the spatial regression, three steps are taken in order. First of all, we start by creating a linear model object for the baseline Ordinary-Least-Square regression, and Morans I test on the residuals in these regressions. Second, I am taking the Lagrange Multiplier Test Statistics to identify the most appropriate alternative model, and allow the difference between spatial error models and spatial lag models. Lagrange Multiplier Test gives incentive to choose between the spatial lag and spatial error model (depending on the significance of the `LRMlag/RLMlag`, `LRMerr/RLMerr` value of the Spatial Durbin Model. Finally, the spatial lag and spatial error model outputs are provided to compare with the baseline OLS model.

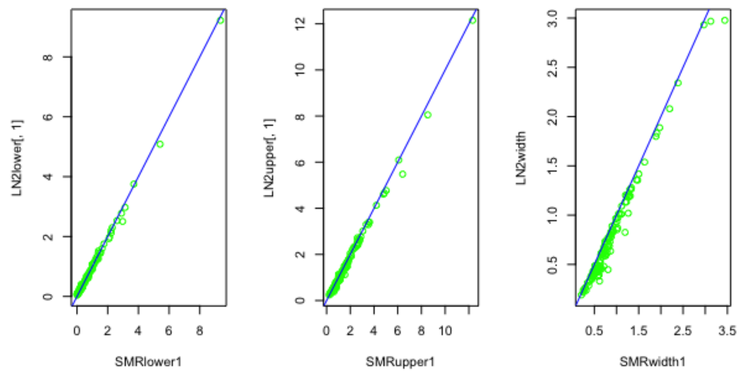

Figure 16: Spatial ICAR model

Variable	Type of Crime	SE	t
OLS Regression: Robbery			
(Intercept)	-87.82495	45.63807	-1.924 .
pov	0.43784	0.07244	6.044 ***
hetero	0.91961	0.47897	1.920 .
nohs	0.09123	0.07330	1.245
OLS Regression: Shoplifting			
(Intercept)	-3644.3940	1628.0838	-2.238 *
pov	10.0276	2.5842	3.880 ***
hetero	37.9156	17.0866	2.219 *
nohs	0.1037	2.6150	0.040
OLS Regression: Burglary			
(Intercept)	369.9582	82.4202	4.489 ***
pov	-0.1985	0.1308	-1.517
hetero	-3.5841	0.8650	-4.143 ***
nohs	0.5017	0.1324	3.790 ***
OLS Regression: Damage			
(Intercept)	-574.7082	298.0909	-1.928 .
pov	2.6899	0.4731	5.685 ***
hetero	6.1413	3.1284	1.963.
nohs	-0.1979	0.4788	-0.413.
OLS Regression: Homicide			
(Intercept)	-10.151863	5.208515	-1.949.
pov	0.037531	0.008267	4.540***
hetero	0.105067	0.054663	1.922 .
nohs	0.025569	0.008366	3.056 **
OLS Regression: Assault			
(Intercept)	-1996.8341	610.2734	-3.272**
pov	6.4692	0.9687	6.678***
hetero	20.7985	6.4048	3.247**
nohs	-1.0773	0.9802	-1.099

Table 1: OLS Regression Baseline Model

It is obvious from the OLS model that which demographic variable is a significant covariate to crime of a specific type, This model assumes no spatial effects, but provide information that are useful in spatial regression. For example, a census tract's poverty level is significantly correlated with robbery, shoplifting and assault, but not so much in others. Education attainment is only relevant to burglary and homicide. neighborhood heterogeneity is most significatly related to the homicide and burglary. After the baseline model, we then proceed to the Moran's I and the Lagrange Multiplier test.

Type of Crime	Spatial Autocorrelation	Spatial Dependence
Robbery	***	**
Burglary	***	**
Shoplifting	$\times$	*
Damage	$\times$	$\times$
Homicide	***	**
Assault	***	*

Table 2: Moran's I and Lagrange Dependence

The spatial dependence and spatial autocorrelation are two separate concepts: spatial autocorrelation mostly refers to "how the neighborhood areas of one area respond by having similar values in an observation", while spatial dependence mostly refers to "how much of the variation of an observation explained by the spatial factors." At census tract level, robbery, burglary, homicide and assault are both spatially dependent and spatially diffusive. Shoplifting (weakly) depends on particular spatial regime, but it does have spatial randomness. Property damage is not spatially dependent and diffusive for the city of Seattle.

Type of Crime	Spatial Lag	Spatial Error	ML Spatial Residual
Robbery	Poverty (52); Heterogeneity (147)	$\times$	***
Theft	Poverty (96); Heterogeneity (434)	$\times$	***
Burglary	Heterogeneity (387)	$\times$	***
Homicide	Poverty (4.2); Education (1.5); Heterogeneity (15.3)	$\times$	$\times$
Assault	Poverty (86); Heterogeneity (313)	$\times$	$\times$

Table 3: Spatial Lag Model and Spatial Error Model

Table 3 shows the model selection of spatial lag model versus spatial error model for the five major types of crime that are significant over spatially. If the Spatial Durbin Model chooses the spatial lag model to be the better-fit model, The parentheses followed each variable under the spatial lag model shows the relative impact score of that variable over that type of crime after the consideration of spatial lag effects. If the Spatial Durbin Model chooses the spatial error model to be the better-fit model, the parantheses followed each variable under the spatial error model will demonstrate the error contributed. In both possibilities, only the variables with significant p-values ($p < 0.05$) will be shown. The ML Spatial residual part shows the significance of spatial residual under the maximum likelihood estimation. All and only the property-related crimes have spatial residual, means there are spatial patterns left unexplained for these three types of crimes.

5 Discussion

This paper discusses the spatial patterns of crimes differentiated by the type of crime, the geographical unit of analysis and the selection of covariates. Findings suggest the "spillover" effects of crime are more salient for property-related crimes, crimes for the sole purpose of physical or material harm have weaker diffusion, especially in larger geographical unit of analysis. Crimes that demonstrate the strongest power of diffusion are those motivated for resources one feel entitled but is deprived of, whereas crimes that demonstrate weaker diffusion activities are those located within a strong regional subculture. Poverty becomes the main reason not only why robbery *occurs*, but also why robbery *diffuses*, whereas burglary are targetting for monetary gain, the choice of target is mainly depending on the *heterogeneity measures*, which highlight a community's collective efficacy. Findings alike in this paper integrates different theoretical frameworks well (rational choice, anomie and social disorganization). The innovation of this paper is to use the same unit of analysis to compare different types of crime under the same setting. This greatly reduces the biases created by using different dataset and different standards. The other advantage of this paper is to cross-compare the different geographical units of analysis, and demonstrate how and why some crimes diffuse over only a small region, but not the larger region. [**Note that due to the limitation of the space, I did not include this part for this final project**]

The development of spatial analysis contribute to criminology in helping us understand not only how crimes diffuse over the space and some of the correlates, but also why crimes diffuse in the way demonstrated. In my paper, I provided not only the significant variables, but also how much their impact and variability changed when the spatial factors kicked in. The extended discussion of these findings may well have impacts on theoretical criminology.

There are frequent debates about the choice of geograhical scale: the larger geographical unit of analysis (UoA) has less problems such as ”temporary migration” (one live in Place X but commit/suffer from a crime in Place Y) but the relative risk summaries is likely to be distorted for the large aggregation of individual (and more seriously, heterogeneous) sum of risks (Wakefield et al., 2000). Smaller UoA may offer localized effects, while larger UoAs offer greater contrasts in relative risks and exposures (-,2000). Understanding the ”UoA” problem not only helped us to detect the ”missing activities” but also challenged the future researchers in studying why certain crimes diffuse in only a small extent, whereas others diffuse in a larger extent. I try to provide some answers in this article, but the answer may be better answered with a higher quality dataset.

6 Reference

Anselin, L. (1995). Local indicators of spatial association LISA. Geographical Analysis, 27, 93115.

Anselin, L. (2010) Spatial Regression Analysis in R A Workbook

Belsley, D. A., K. E. and Welsch, R. E. (1980). Regression Diagnostics. Wiley, New York.

Elliott, P., Wakefield, J. C., Best, N. G., and Briggs, D. J. (2000). Spatial Epidemiology: Methods and Applications. Oxford University Press, Oxford.

Geary, R. (1954). The contiguity ratio and statistical mapping. The Incorporated Statistician, 5, 115145.

McCullagh, P. and Nelder, J. (1989). Generalized Linear Models, Second Edition. Chapman and Hall, London.

Moran, P. (1948). The interpretation of statistical maps. Journal of the Royal Statistical Society, Series B, 10, 243251.

Agresti, A. and Coull, B. A. (1998). Approximate is better than exact for interval estimation of binomial proportions. The American Statistician, 52, 119126.

Besag, J. (1974). Spatial interaction and the statistical analysis of lattice systems. Journal of the Royal Statistical Society, Series B, 36, 192236.

Besag, J., York, J., and Mollie, A. (1991). Bayesian image restoration with two applications in spatial statistics. Annals of the Institute of Statistics and Mathematics, 43, 159.

Clayton, D. and Kaldor, J. (1987). Empirical Bayes estimates of age-standardized relative risks for use in disease mapping. Biometrics, 43, 671682.

Elliott, P., Wakefield, J. C., Best, N. G., and Briggs, D. J. (2000). Spatial Epidemiology: Methods and Applications. Oxford University Press, Oxford.

Fong, Y., Rue, H., and Wakefield, J. (2010). Bayesian inference for generalized linear mixed models. Biostatistics, 11, 397412.

Kemp, I., Boyle, P., Smans, M., and Muir, C. (1985). Atlas of Cancer in Scotland, 19751980: Incidence and Epidemiologic Persepctive. IARC

Wakefield, J. (2004). A critique of statistical aspects of ecological studies in spatial epidemiology. Environmental and Ecological Statistics, 11, 3154.

Wakefield, J. (2007). Disease mapping and spatial regression with count data. Biostatistics, 8, 158183.

Wakefield, J. (2008). Ecologic studies revisited. Annual Review of Public Health, 29, 7590.

Andresen, Martin A. and Nick Malleson. 2015. ”Intra-Week Spatial-Temporal Patterns of Crime.” Crime Science 4(1):1-11.

Anselin, Luc. 2014. SpaceStat: a software package for the analysis of Spatial Data. Version 4.0 Ann Arbor, M.I.: BioMedware

Anselin, Luc, Ibnu Syabri and Youngihn Kho. 2006. GeoDa: An Introduction to Spatial Data Analysis. Geographical Analysis 38 (1), 5-22.

Anselin, Luc. 2005. Exploring Spatial Data with GeoDa: A Wookbook UC Santa Barbara, CA: Center for Spatially Integrated Social Science.

Anselin, Luc and Serge Rey. 1991. "Properties of Tests for Spatial Dependence in Linear Regression Models." Geographical Analysis 23(2): 112-131.

Asgary, Ali, Ali Hajinezhad, Issa Bartaw and Ali Goli. 2013. "Pattern Analysis on Residential Burglary by Exploratory Spatial Data Analysis (ESDA), Case Study: Zahedan City." Security and Social Order Strategic Studies Journal 6(2):1-3.

Baller, Robert D., L.Anselin, Steven F. Messner, Glenn Deane and Darnell F. Hawkins. 2001. "Structural Covariates of U.S. County Homicide Rates: Incorporating Spatial Effects." Criminology 39(3):561-88.

Bones, Paul D. C. and Trina L. Hope. 2015. "Broken Neighborhoods: A Hierarchical Spatial Analysis of Assault and Disability Concentration in Washington, DC." Journal of Quantitative Criminology 31(2):311-29.

Breetzke, Gregory Dennis. 2012. "The Effect of Altitude and Slope on the Spatial Patterning of Burglary." Applied Geography 34:66-75.

Ceccato, Vnia, and Dietrich Oberwittler. 2008. "Comparing Spatial Patterns of Robbery: Evidence from a Western and an Eastern European City." Cities 25(4):185-96.

Charlton, Martin, A Stewart Fotheringham and Chris Brunsdon. 2008. GWR Workbook. National Center for Geocomputation, National University of Ireland.

Deane, Glenn, E. M. Beck and Stewart E. Tolnay. 1998. "Incorporating Space into Social Histories: How Spatial Processes Operate and How We Observe Them." International Review of Social History 43(S6):57-80.

Deane, Glenn, Steven F. Messner, Thomas D. Stucky, Kelly McGeever and Charis E. Kubrin. 2008. "Not 'Islands, Entire of Themselves': Exploring the Spatial Context of City-Level Robbery Rates." Journal of Quantitative Criminology 24(4):363-80.

Fotheringham, A.S. and Wong, D.W.S. 1991. The modifiable areal unit problem in multivariate statistical analysis. Environment and Planning A 23, 1025-1044

Harper, Dee Wood, David N. Khey and Gwen Moity Nolan. 2013. "Spatial Patterns of Robbery at Tourism Sites: A Case Study of the Vieux Carr in New Orleans." American Journal of Criminal Justice 38(4):589-601.

Homel, Ross, Janet Chaseling and Michael Townsley. 2000. "Repeat Burglary Victimisation: Spatial and Temporal Patterns." Australian and New Zealand Journal of Criminology, 33(1):37-63.

Livingston, Michael. 2008. "Alcohol Outlet Density and Assault: A Spatial Analysis." Addiction 103(4):619-28.

Lundrigan, Samantha, Sarah Czarnomski and Marc Wilson. 2010. "Spatial and Environmental Consistency in Serial Sexual Assault." Journal of Investigative Psychology and Offender Profiling 7(1):15-30.

Messner, Steven F., Luc Anselin, Robert D. Baller, Darnell F. Hawkins, Glenn Deane and Stewart E. Tolnay. 1999. "The Spatial Patterning of County Homicide Rates: An Application of Exploratory Spatial Data Analysis." Journal of Quantitative Criminology 15(4):423-50.

Morenoff, Jeffrey D., Robert J. Sampson and Stephen W. Raudenbush. 2001. "Neighborhood Inequality, Collective Efficacy, and the Spatial Dynamics of Urban Violence." Criminology 39(3):517-58.

Nakaya, Tomoki. 2008. ”Geographically Weighted Regression (GWR).” In Encyclopedia of Geographic Information Science, edited by Karen K. Kemp, 180-85. Thousand Oaks, CA: SAGE Publications, Inc.

Nivette, Amy E. 2012. ”Spatial Patterns of Homicide and Political Legitimacy in Europe.” International Journal of Comparative and Applied Criminal Justice 36(3):155.

Painter-Davis, Noah. 2012. ”Structural Disadvantage and American Indian Homicide and Robbery Offending.” Homicide Studies.

Rotton, James and Ellen G. Cohn. 2004. ”Outdoor Temperature, Climate Control, and Criminal Assault: The Spatial and Temporal Ecology of Violence.” Environment and Behavior 36(2):276-306.

Socia, Kelly M. 2013. ”Too Close for Comfort? Registered Sex Offender Spatial Clustering and Recidivistic Sex Crime Arrest Rates.” Sexual Abuse: A Journal of Research and Treatment 25(6):531-56.

Taylor, Ralph B. 2015. Community Criminology: Fundamentals of Spatial and Temporal Scaling, Ecological Indicators, and Selectivity Bias. New York: New York University Press.

Tickamyer, Ann R. 2000. ”Space Matters! Spatial Inequality in Future Sociology.” Contemporary Sociology [H.W. Wilson - SSA] 29(6):805.

Vilalta, Carlos and Robert Muggah. 2014. ”Violent Disorder in Ciudad Juarez: A Spatial Analysis of Homicide.” Trends in Organized Crime 17(3):161-80

7 Appendix: Additional Figures

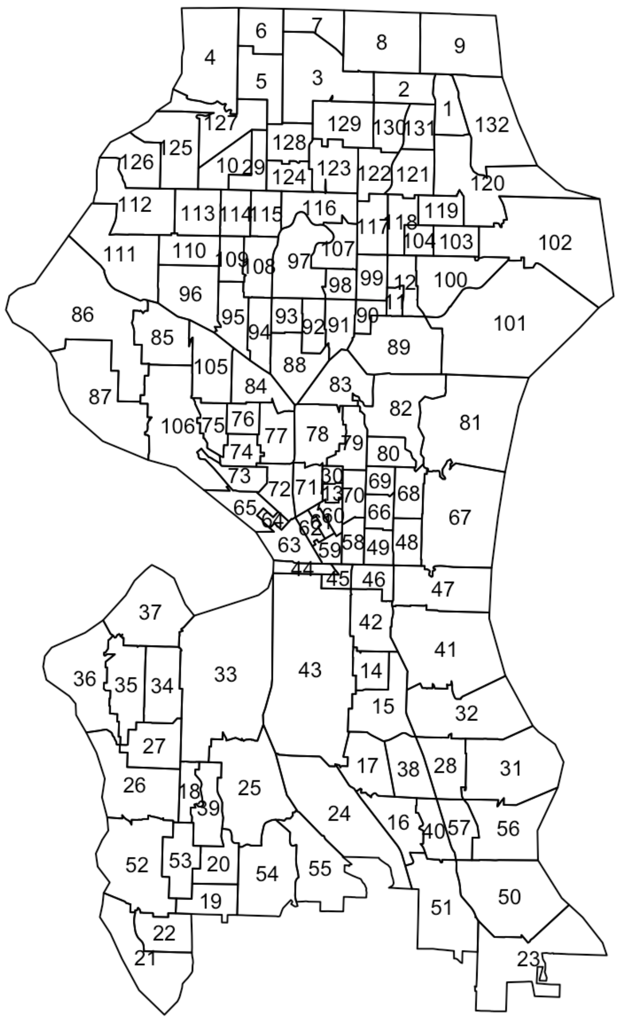

Figure 17: Seattle Codes

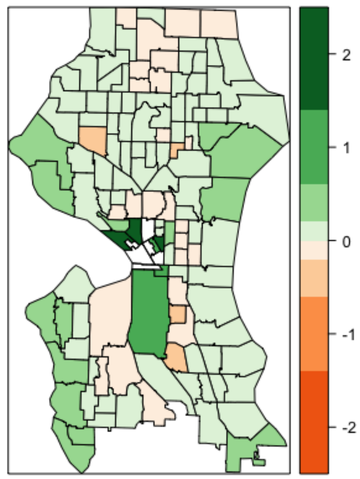

Figure 18: Another example of Local Contribution

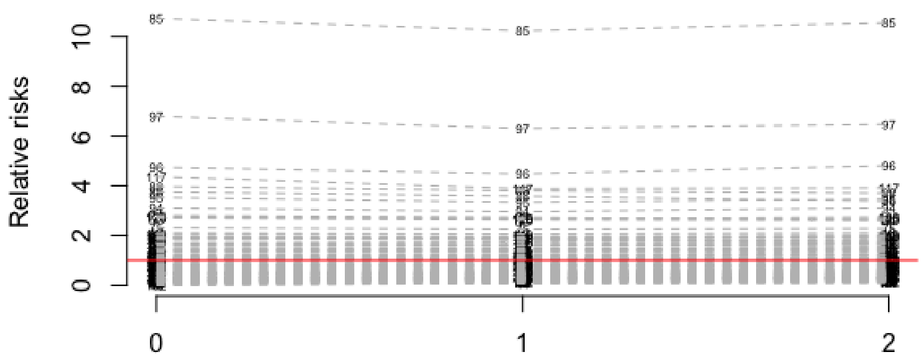

Figure 19: Comparison With/Without Covariate

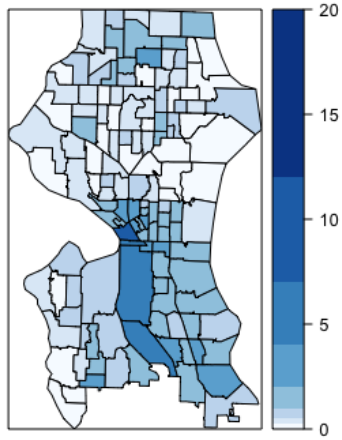

Figure 20: Robbery SMR

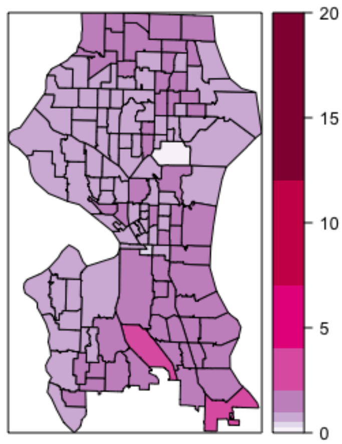

Figure 21: Burglary SMR

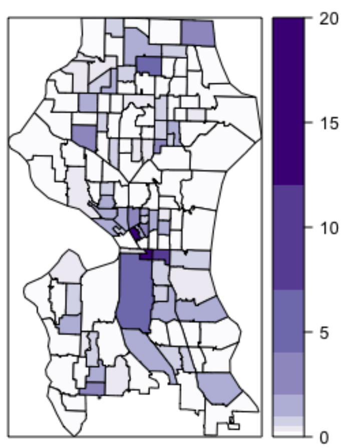

Figure 22: Theft SMR

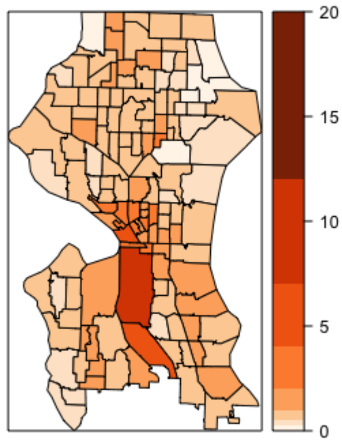

Figure 23: Damage SMR

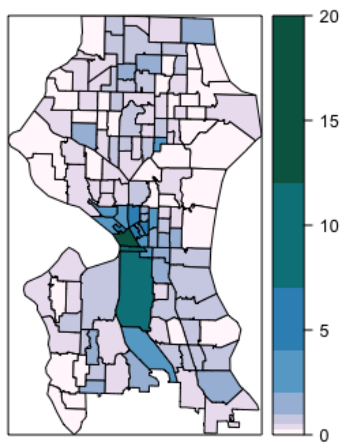

Figure 24: Homicide SMR

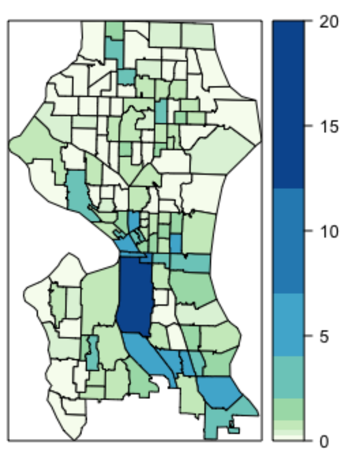

Figure 25: Assault SMR