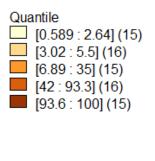
GeoDa Exploratory Analysis

Chicago has historically been a segregated city and continues to be segregated in 2017. While the population of Chicago is roughly split into thirds for blacks, Hispanics, and whites, these populations, similar to crime rates, are not spatially distributed evenly within the city according to census data. These three populations display near perfect segregation, with black populations concentrated in the south and west communities, Hispanics concentrated in the northern communities.



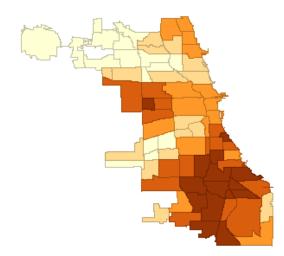
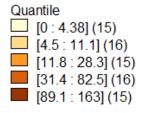


Figure 1 Percent Black



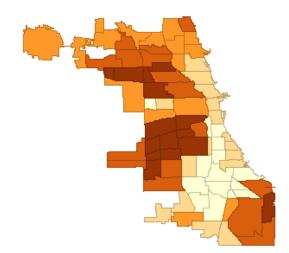
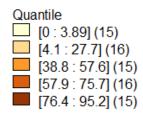


Figure 2 Percent Hispanic



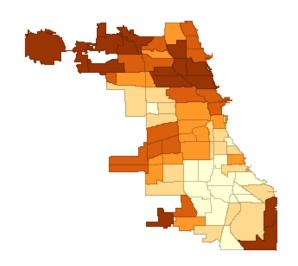


Figure 3 Percent White

Racial demographics are not the only characteristic that exhibits spatial variability; in light of racial segregation, educational attainment and average household income also fall in line with a socioeconomic segregation narrative. Figures 4, 5, and 6 visualize the extremes to which Chicago is segregated economically and with educational attainment. Specifically, higher household incomes are located in the same regions which are occupied by majority whites while lower household incomes are associated with black and Hispanic populations. These same economic disconnects are seen in age 25 and older population educational attainment.

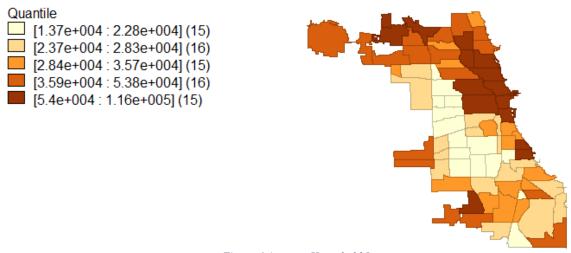


Figure 4 Average Household Income

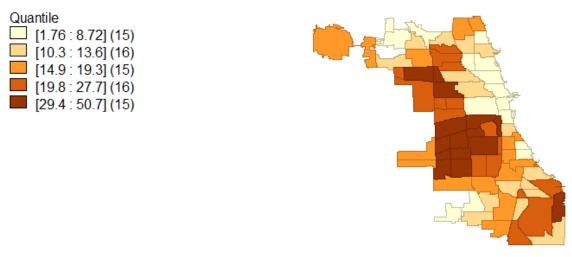


Figure 5 Percent Population Less High School

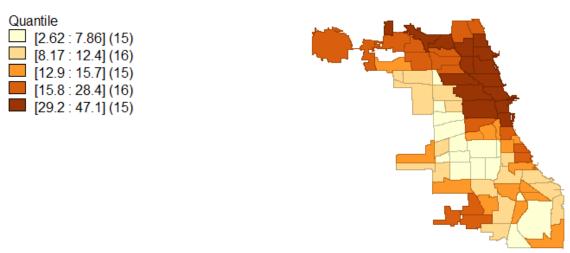


Figure 6 Percent Population Bachelor's Degree

Finally, as was alluded to by the University of Chicago Crime Lab's gun violence report as well as the Chicago Police Department and numerous Chicago media outlets, Chicago crime is disproportionately concentrated in these areas of high black and Hispanic populations with low educational attainment and low incomes. Violent crime rates in figure 7 and homicide rates in figure 9 bring further evidence to the claim that Chicago's violent crimes and murders occur in primarily black and Hispanic neighborhoods with low income and education. Property crimes, in figure 8, tell a slightly different story since these crimes are more prolific in areas with more wealth and property value, like Chicago's Loop area.

Quantile [192 : 461] (15) [469 : 677] (16) [681 : 1.22e+003] (15) [1.24e+003 : 2.25e+003] (16) [2.29e+003 : 6.31e+003] (15)

Figure 7 Violent Crime Rates per 100,000

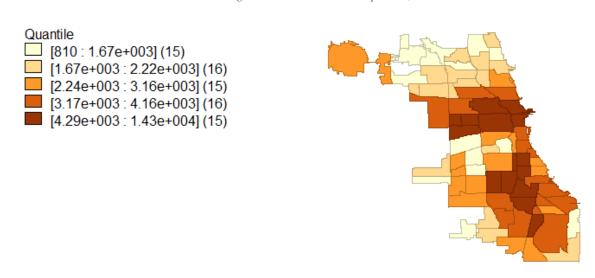


Figure 8 Property Crime Rates per 100,000

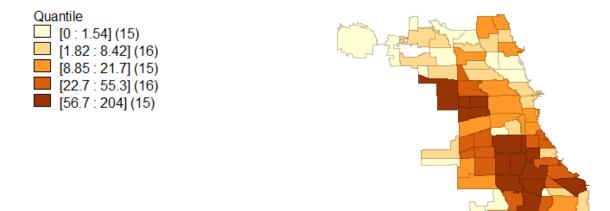


Figure 9 Homicide Rates per 100000

311 call rates, represented in figure 10, present a different narrative than one would imagine in the context of Chicago's crime rates and population demographics. As far as what can be taken at face value from these figures, there does not appear to be any patterns or clusters of 311 call rates in an area. If communities were to have high collective efficacy and be proactive in keeping their neighborhood in order, then we would expect the areas with either high violent and high property crimes or low violent and property crimes to be calling the city of Chicago at the highest rates. Instead, we see a dispersed rate of 311 calls incongruent to property crime locations and only partially reflective of violent crimes and homicides.

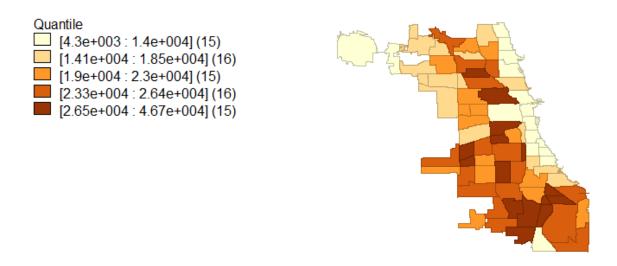
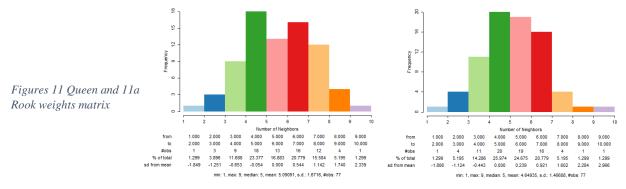


Figure 10 311 Call Rates per 100,000

I. Spatial Analysis

In the exploratory analysis, I utilized quantile maps to visually investigate whether certain community area characteristics were clustering in specific areas of the city. To create a more scientific determination of clustering, I conducted global and local Moran I and Local Getis-Ord Gi* (G-i-star) analyses. As a precursor to these analyses, I experimented with three different spatial weight matrixes, queen contiguity, rook contiguity, and 5 nearest neighbors. Figures 11 and 11a show histograms of both the queen and rook contiguity weights (since nearest neighbor weights produced a flat graph it was not included); I determined that a rook spatial weight matrix was the best fit for the data since it most closely resembled a normal distribution and the connectivity map for the queen weights produced undesirable neighbors.



To determine spatial autocorrelation, that is how grouped similar and dissimilar values are to one another, global Moran's I tests were ran on the variables presented in the exploratory analysis with rook contiguity as the weights matrix. To no surprise, racial demographics produced highly positive values: black = 0.71, Hispanic = 0.61, and white = 0.69. Similarly, average household income, percent of population with less than a high school education, and percent of population with a bachelor's degree had high positive Moran's Index values at 0.59, 0.56, and 0.72 respectively. Finally, criminal activity exhibited spatial autocorrelation in its Moran's I values; Violent crime produced a 0.52 index, property crime produced a 0.37 index and homicides produced a 0.47 index. 311 call rate spatial autocorrelation was less pronounced, with a Moran's I value of 0.39. Overall, we see spatial autocorrelation high for racial demographics and bachelor's degrees at around a 0.7 Moran's I value while income and low education producing slightly lower values and crimes even more. However, violent crimes are systematically more spatially autocorrelated than property crimes and 311 call rates exhibit the lowest spatial autocorrelation of the variables.

Global Moran's I is limited, producing results which only determine if the entire spatial study area is autocorrelated; therefore, in order to determine which community areas have spatial autocorrelation and clustering, local Moran's I and Gi* tests were ran. Beginning with 311 call rates, figure 12 and 12a displays the results of these tests. We can see that statistically significant (p < 0.05) highly similar 311 call values and hot spots are largely present in the west community areas and 3 communities in the south. Meanwhile, dissimilar cold spots exist along the lake in communities like the Loop. For violent and property crimes, the local Moran's I and Gi* tests show that the most northern communities represent dissimilar and cold locations in terms of crime rates. At the same time, violent and property crime hot spots and similar values

are located in the areas we would expect, specifically the south and west for violent crimes (homicides matched these trends) and around the loop and some areas of the south for property crimes, see figures 13 and 14. It's worth mentioning that average household income, less than high school education and bachelor's degree local Moran I's and Gi*'s similar/dissimilar and hot/cold spot values paralleled the findings from the exploratory analysis. In the interest of brevity, I decided not to include those maps.

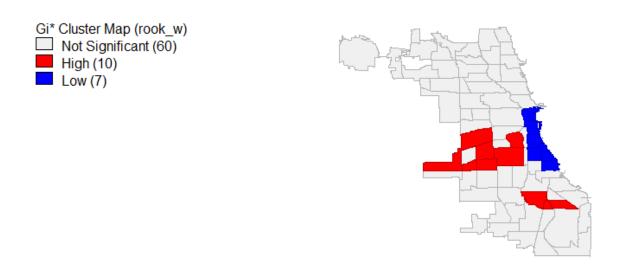


Figure 12 311 Call Rates Gi*

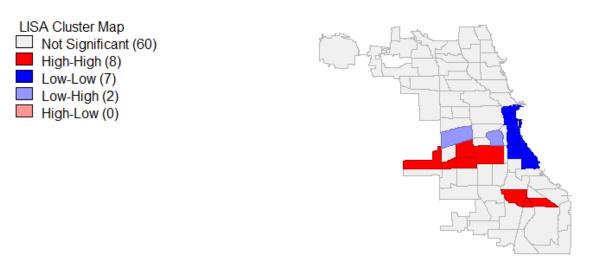


Figure 12a 311 Call Rates Local Moran's I

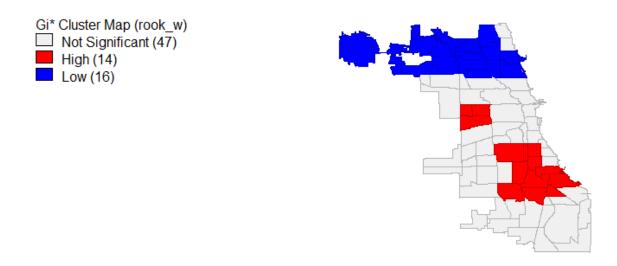


Figure 13 Violent Crime Rates Gi*

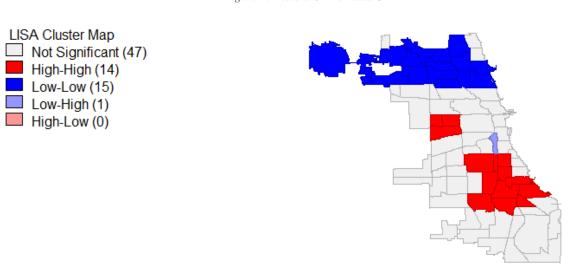


Figure 13a Violent Crime Rates Local Moran's I

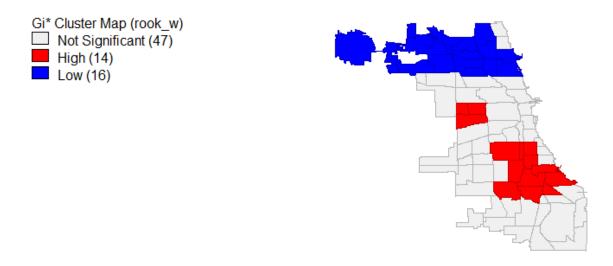


Figure 14 Property Crime Rates Gi*



Figure 14a Property Crime Rates Local Moran's I

In the final section of this analysis, I assessed the spatial regression models used in this analysis. Model 1 was an OLS regression model with 311 call rates as the dependent variable and the independent variables as violent crime, property crime, white, black, Hispanic, average household income, less than high school education, and bachelor's degree incorporating the rook contiguity spatial weights matrix.

$$\hat{y} = b_0 + b_1 x_{vcrime} + b_2 x_{pcrime} + b_3 x_{pct_{white}} + b_4 x_{pct_{black}} + b_5 x_{hispanic} + b_6 x_{avg_hh_inc} + b_7 x_{less_{hs}} + b_8 x_{bach} + \varepsilon$$

Based on Model 1's diagnostics for spatial dependence results in which the Robust LM (error) test was not significant, I determined that a spatial error test would be appropriate this Model 2.

 $Table\ 1$

N = 77	Model 1			Mod		
Variables	В	SE B	p	В	SE B	p
Constant	24851.80	11231.10	0.03**	31133.5	10636.6	0.00***
Violent Crime	2.81	2.41	0.25	3.60	2.09	0.08*
Property Crime	-0.25	0.84	-0.29	-0.09	0.70	0.90
Pct White	24.22	98.28	0.25	-57.98	93.71	0.54
Pct Black	21.74	90.95	0.24	-63.37	87.41	0.47
Pct Hispanic	124.28	51.82	0.02**	92.78	44.13	0.04*
Avg HH Income	-0.9	0.84	0.10	-0.11	0.09	0.20
Pct Less than High School Education	-443.91	263.93	-1.68	-523.08	222.27	0.02*
Pct With Bachelor's Degree	-117.20	195.39	-0.60	8.59	221.97	0.97
Lambda				0.62		0.00***
R^2		.23		.42		
Adjusted R ²		0.15				

^{*} p < 0.05, **p < 0.01

Reviewing Table 1's regression outputs, there is generally weak evidence that this model is effective in explaining the variation in Chicago's 311 call rates. In Model 1, the only statistically significant independent variable is percent Hispanic with a positive coefficient of 124.28, suggesting that a larger Hispanic population is predictive of higher 311 call rates. Meanwhile, in the spatial error model we see violent crime, percent Hispanic, and percent with less than a high school education as statistically significant. This model gains more predictive power than Model 1 in its ability to predict how often a community area calls 311. Violent crime and percent

Hispanic have positive coefficients while percent less than high school education has a negative coefficient, suggesting that higher crime rates and higher Hispanic populations are associated with greater 311 call rates while lower percentages of the population with less than high school education are associated with 311 call rates. Overall, both models perform poorly in predicting how often a community area calls 311 for local government services. Reviewing the R² values for the two models, we see a small value for Model 1, 0.23, and nearly an increase of 50% for the spatial error model, 0.42. However, the majority of both models are not statistically significant so caution should be taken when considering the R² values.