Examining the Correlation between Neighbourhood Property Crime Rates and Social Factors in Toronto, ON

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This paper reports our analysis of property crime rates in Toronto, ON and their correlation with population density, income, race, and age by neighbourhood. Data were retrieved from The City of Toronto Open Data Portal.

Keywords: crime, social factors, spatial analysis

Introduction

In most cities worldwide, property crime is listed as the most common criminal offence. (Thatcher 2015). Larceny consisting of burglary, auto theft, and other forms of theft are seen the most frequently when gauging property crime. The conflict theory denotes that crime as an offence is a result of various types of material inequality, often governed by disparities within different socioeconomic strata. (Nickerson 2019). Continually, the social disorganization theory is derived from the idea that physical signs of neighbourhood disorder such as broken windows, inadequate lighting, and vacant housing, play a role in the presence of crime within an area. (He, Páez, and Liu 2017). Both theories highlight the link of socioeconomic factors and disparitie and the presence of crime. The aim of this study is to examine the following research question: What is the relative risk of property crime in various Toronto, ON neighbourhoods, and how strong is this correlation when compared to socioeconomic factors such as, income, age, race, and population density. Open datasets obtained from the City of Toronto as well as The Toronto Open Data Portal will be visualized using a combination of regression modelling, Moran's I tests, and spatial data visualizations will be used to help quantify the above question.

Background

Within Toronto, the gap between economic classes has been at a steady incline. Between the years of 1980 to 2005, income inequality within the city had risen nearly 31% percent, the largest increase in any Canadian major city. (Hulchanski 2011). The distinct economic divide found within the city is just one of the reasons Toronto has been nicknamed "the city of neighbourhoods" (Van Ingen, Khandor, and Fleiszer 2015), the well defined social, and economic variability amongst Toronto's neighbourhoods are polarizing realities from the outside looking in. However, this differentiability between neighbourhood hints to further correlations between income and additional social factors. In a study done by David Hulchanski at the University of Toronto, 2016 census data was used to investigate the ineluctable link between income polarization, and racial demographics in Toronto. Findings from the study modelled that 48% of Toronto's census tracts were considered low income with annual average income being $32,000 before taxes, additionally, it was found that 68% of individuals living in these low-income tracts were part of a racialized group, or other visible minority. (Hulchanski 2011).

Over the past few decades, theories of crime have gone through extensive development to gain valuable insight on the constituents of criminal offences and to better understand what might influence individuals of rather normal biological, and psychological nature to commit various crimes. (Longley 2020). Most notably, social disorganization theory, and conflict theory have highlighted the association of socioeconomic factors, like, race, income, and physical environment, to crime rates. These theories back up the notion that the presence of crime is not evenly distributed spatially, but rather, varies as a result of external factors.

The basis of the social disorganization theory suggests that crime is a result of one's physical and social environment. (Bond 2015). A case study conducted in Chicago, Illinois by Robert Park and Ernest Burgess of the Chicago School of Criminology , found that crime rates were unevenly distributed around the city, with a heavy concentration of crime occurring in and around the inner-city. These inner city neighbourhoods were also found to be transitional areas that had generally low socio-economic status, and a large racialized population. In concluding the study, Park and Burgess suggested that the increase rates of crime in these pockets of the city were not a result of "personal attributes" of the occupants of these neighbourhoods, rather the "the structural factors of poverty, high heterogeneity, and high mobility causing what was dubbed "social disorganization." (Kitchen 2006). In understanding race, income, and gender as potential drivers of high crime rates within certain areas of the city, there allows space for the argument of elevated presence of law enforcement and over policing of these boroughs. The duality of this topic allows for multiple vantage points to be investigated implementing varying theories to support.

Study area

The relationship between property crime rates and social factors were studied across the census neighbourhoods of Toronto, ON, Canada (see Figure 1). There are 140 neigbourhoods in total at the time of this study. *write more about why this area was selected after background is done.*

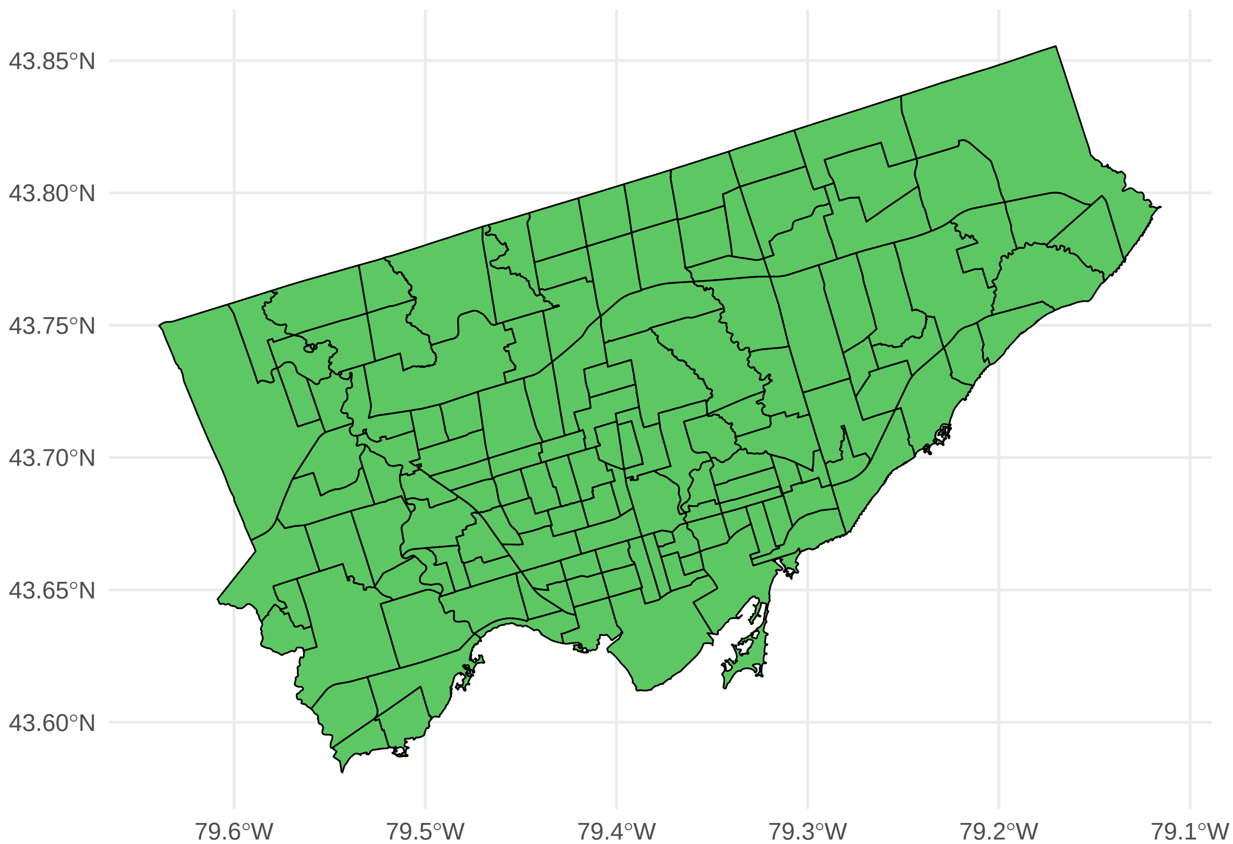

Figure 1: Census Neighbourhoods of Toronto, ON, Canada

Data

The data used in this study comes from the City of Toronto Open Data Portal, accessed using the **opendataportal** package in R. (Gelfand 2020). Two separate datasets were used: *Neighbourhood Crime*

Rates and *Neighbourhood Profiles*. The *Neighbourhood Crime Rates* dataset reports both the raw count and rates per 100,000 of seven different types of crime within the 140 neighbourhoods of Toronto. (Toronto Police Service 2019). Of the seven types of crime, the four reported types of property crime — auto theft, breaking and entering, robbery, and theft over $5000 — were the focus of this study. The *Neighbourhood Profiles* dataset reports the demographic, social, and economic findings of the 2016 census for each of Toronto's 140 neighbourhoods. (Statistics Canada 2021). Select data regarding population density, income, race, and age were utilised as the social factors of interest for this study.

Methods

This study was conducted using the open software language **R** to carry out statistical analyses of crime rates and social factors in the city of Toronto, ON, and visualise these results through the production of maps and figures. Property crime rates by neighbourhood in 2016 were used as the independent variable. This was compared against 4 other variables from 2016 census data at the neighbourhood level: population density, percentage of the population designated as 'low income,' percentage of the population belonging to a visible minority group, and percentage of the population aged 15-29. The areal data of this study was analysed using choropleth mapping to visualize geographic trends, boolean maps relative to a selected values, scatterplots, and regression analyses in order to evaluate the relationship between crime and selected social factors.

Results

First the data of interest was visualised through choropleth maps to gain a general view of any potential trends and create a starting point for further analysis. Figure 2 illustrates the rates of auto theft, breaking and entering, robbery, and theft over $5000 in Toronto's neighbourhoods in 2016, and figure 3 shows the aggregated rate of these 4 types of property crimes.

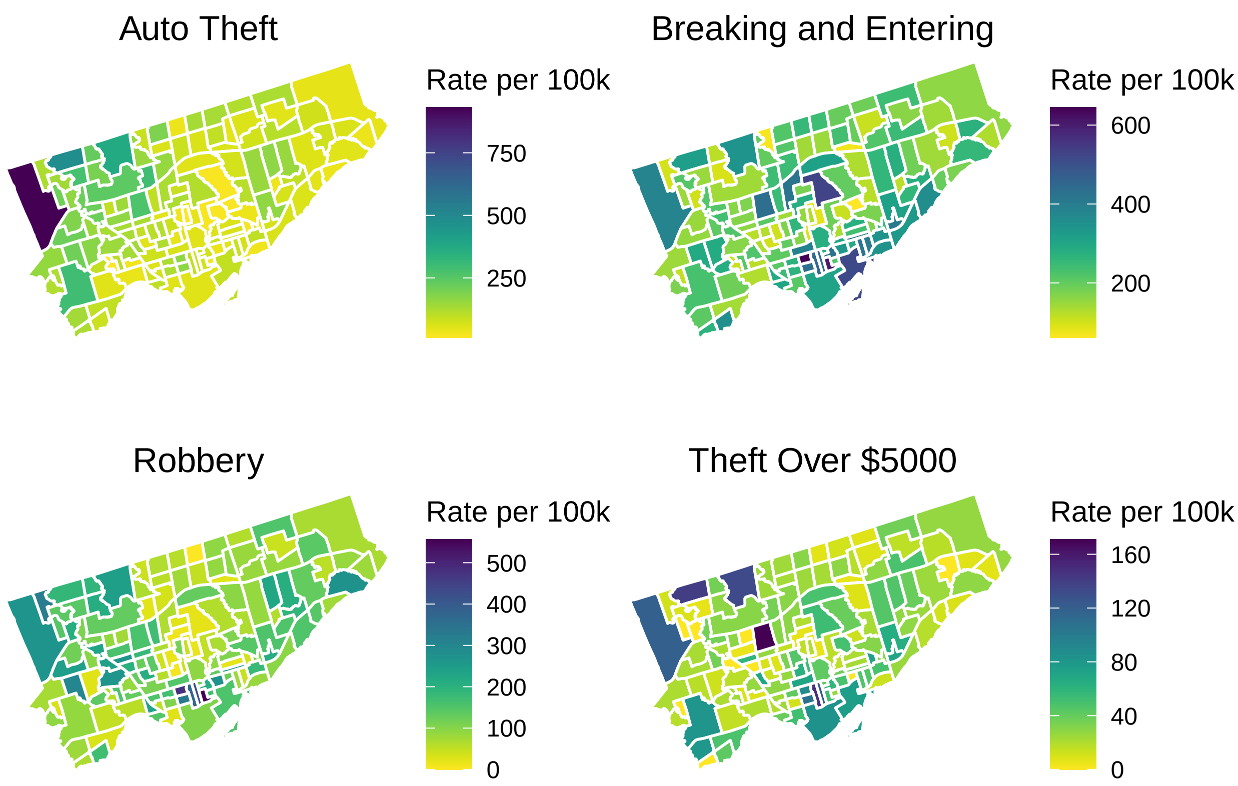

Figure 2: Four categories of property crime rates by neighbourhood (2016)

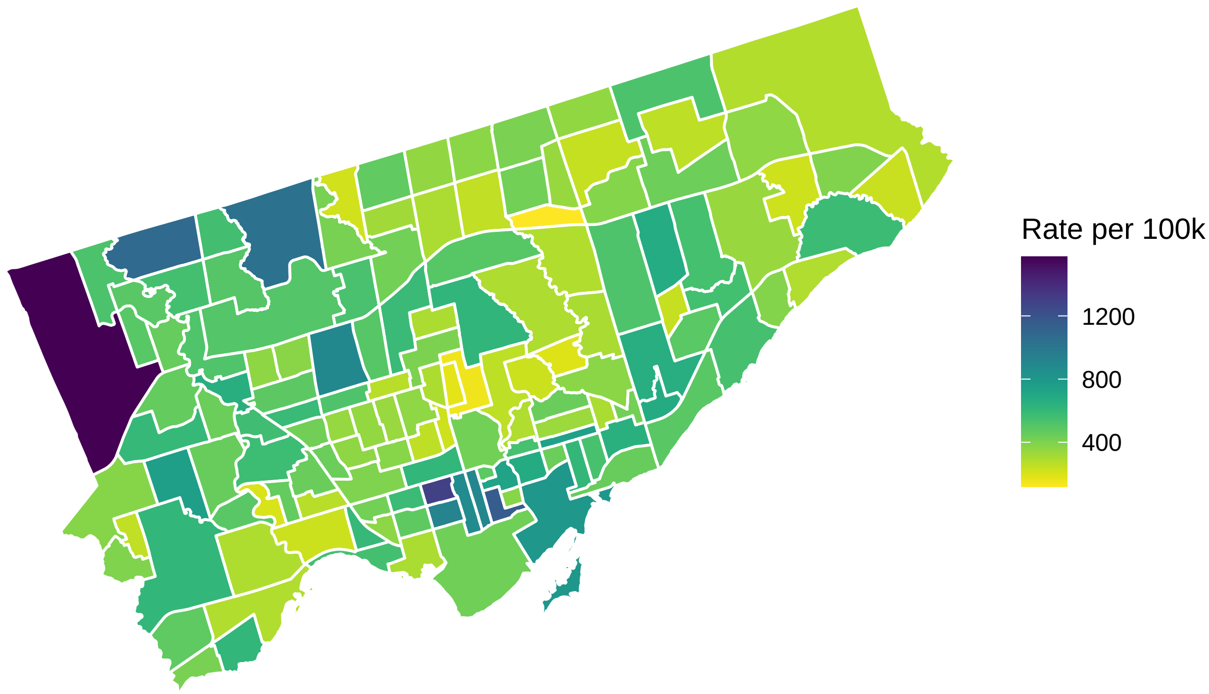

Figure 3: Aggregated property crime rates by neighbourhood (2016)

Figure 4 through figure 7 are choropleth maps denoting the social factors of interest for this study in 2016. Figure 4 denotes population density by neighbourhood. Figure 5 shows the percentage of individuals in each neighbourhood who are categorized as low income after taxation. Figure 6 illustrates the percentage of individuals in each neighbourhood who belong to a visible minority group. Finally, Figure 7 illustrates the percentage of individuals in each neighbourhood who are aged 15-29.

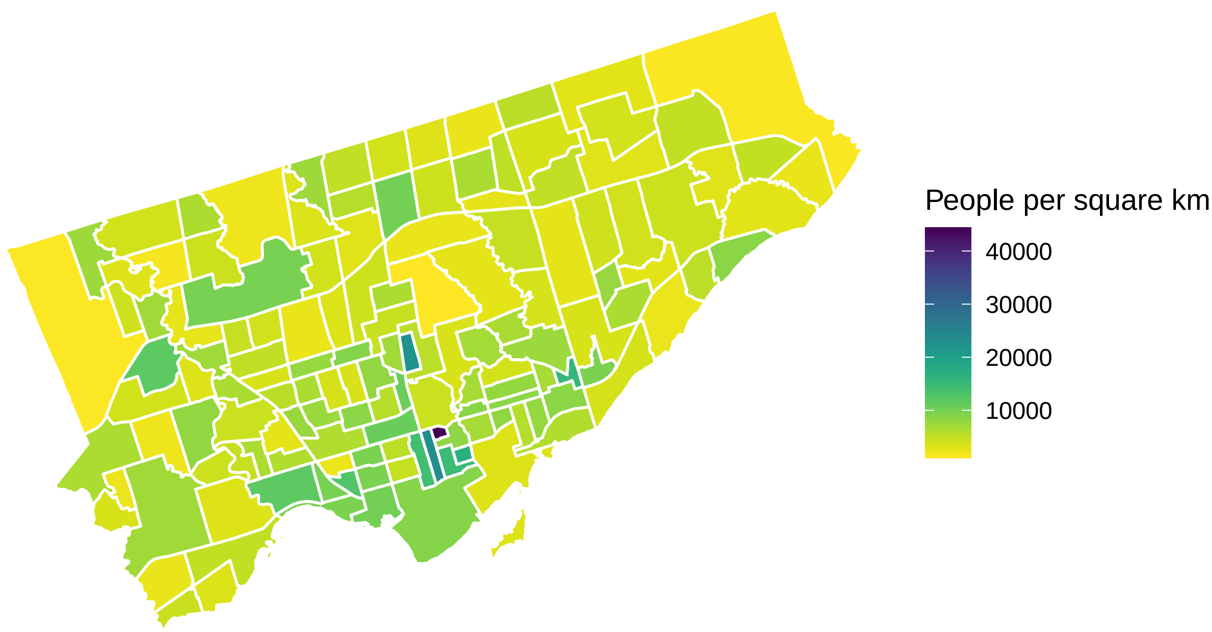

Figure 4: Population density by neighbourhood (2016)

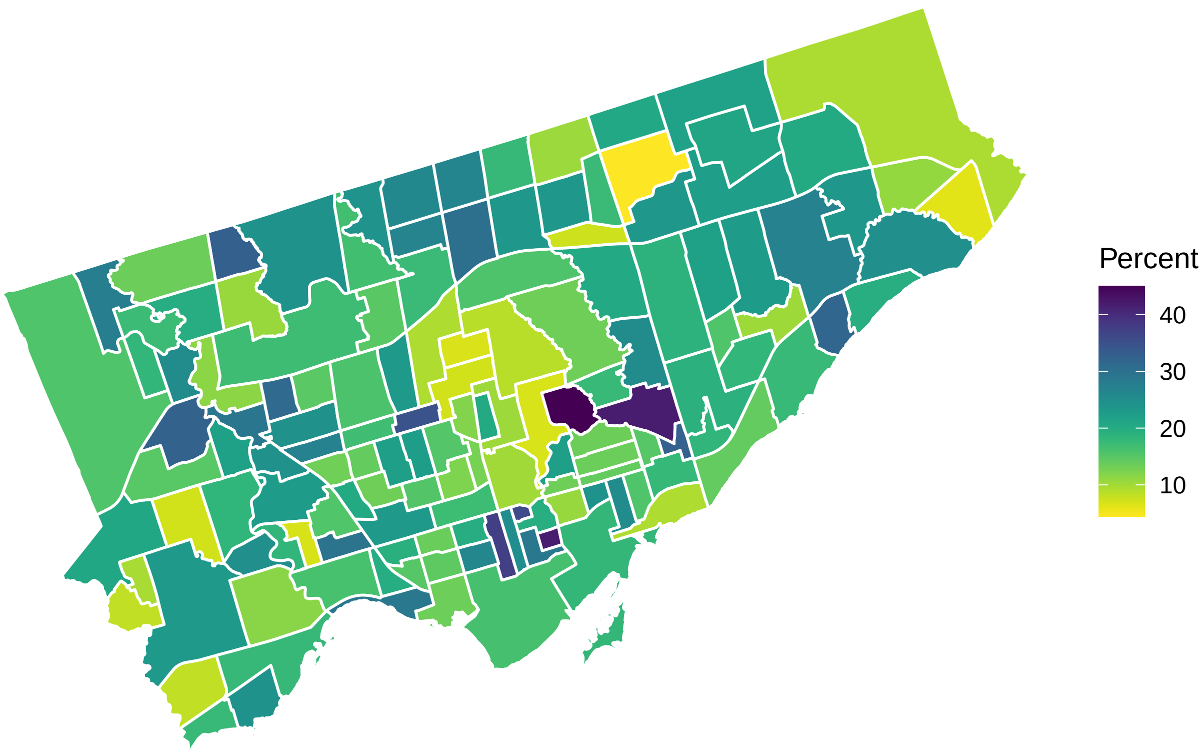

Figure 5: Percentage of inhabitants who have been identified as 'Low Income After Taxation' by neighbourhood (2016)

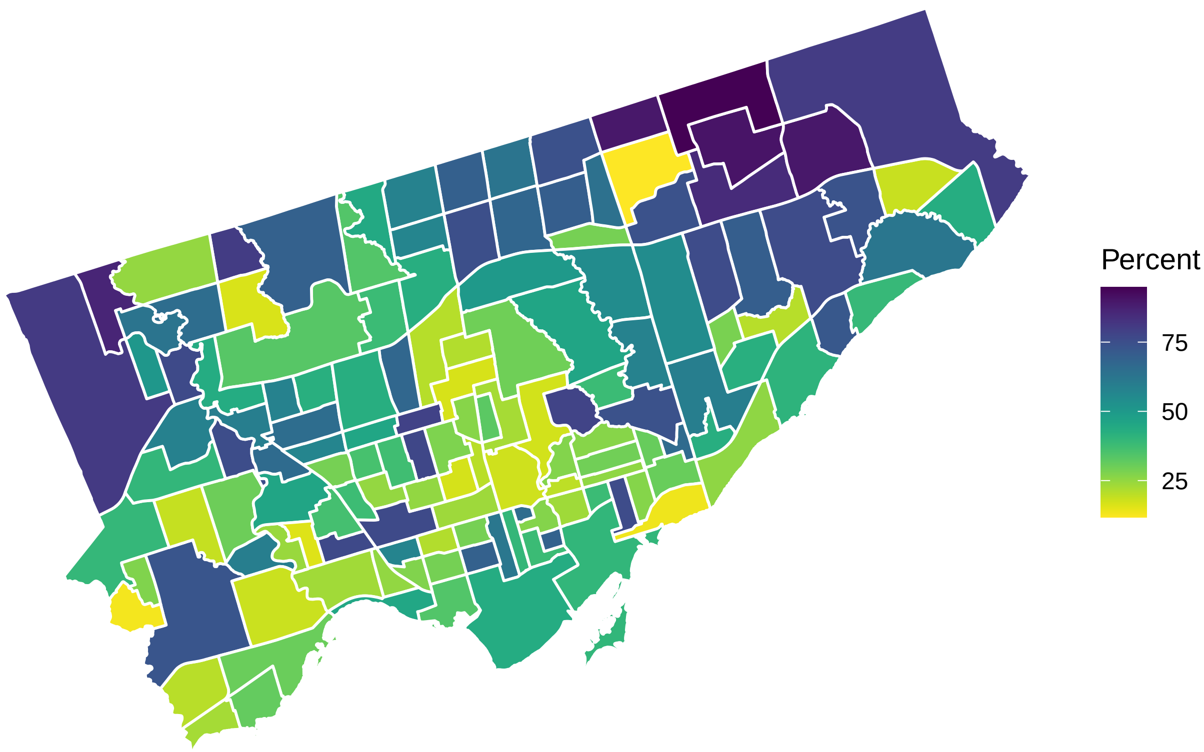

Figure 6: Percentage of inhabitants who belong to visible minority groups by neighbourhood (2016)

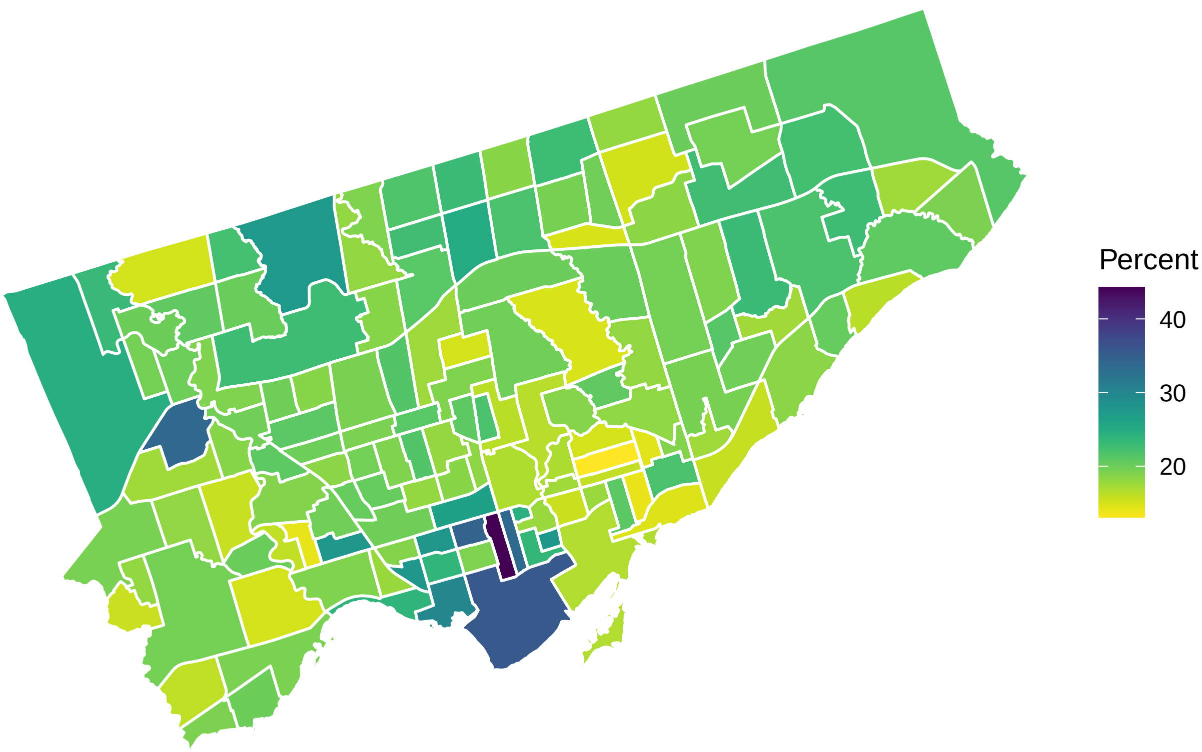

Figure 7: Percentage of inhabitants aged 15-29 by neighbourhood (2016)

Figure 8 is a boolean map indicating which neighbourhoods have property crime rates that are above and below the citywide mean in 2016. This is useful in illustrating potential trends in the data with high-crime or low-crime neighbourhoods being clustered in some form.

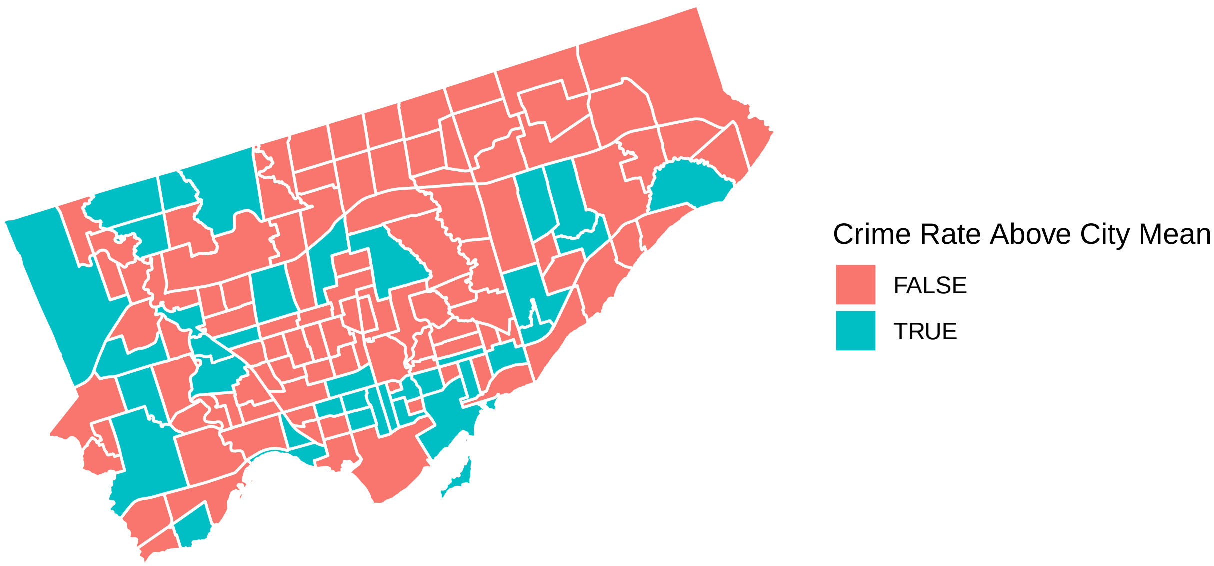

Figure 8: Neighbourhood crime rates relative to mean crime rate of the whole of Toronto (2016)

Figure 9 is a Moran scatterplot for neighbourhood property crime rate in 2016. The value of Moran's I for this dataset is 0.246 with a p-value of 6.197e-08. With these statistics, we can reject the null hypothesis of spatial independence, as Moran's I is large enough to indicate some spatial autocorrelation, and the p-value is small enough to indicate a high degree of confidence.

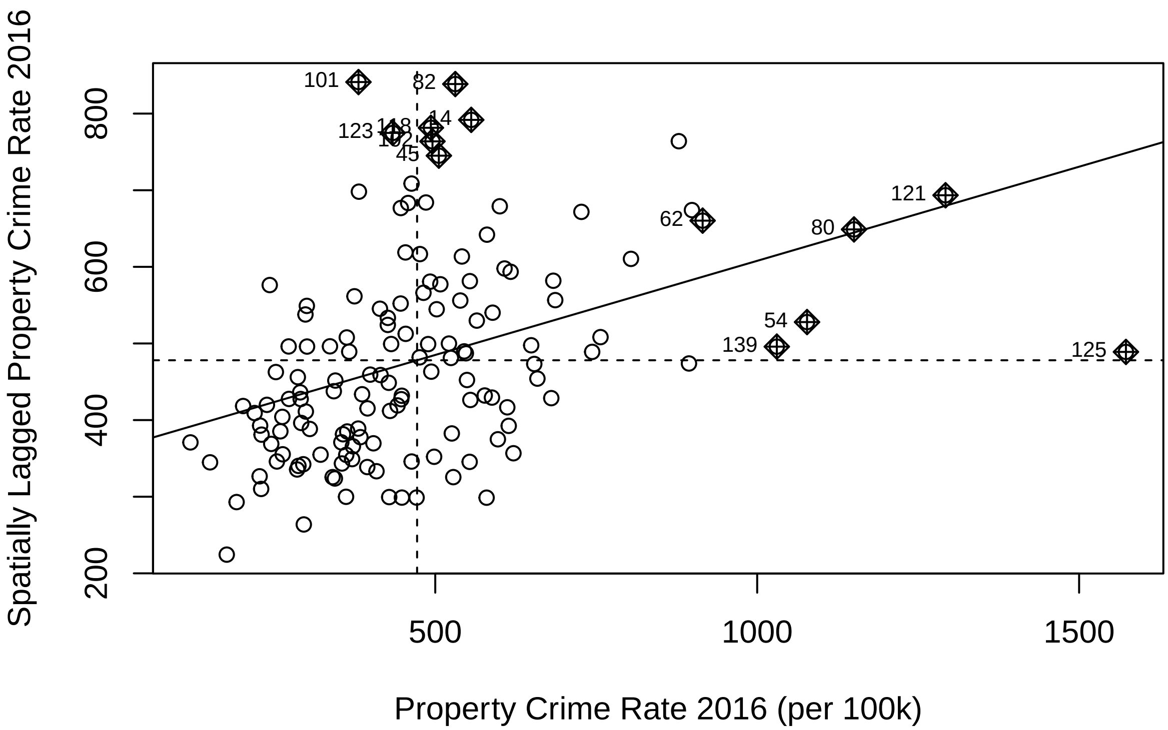

Figure 9: Moran's plot for spatial autocorrelation regarding neighbourhood property crime rates (2016)

Table 1: Property crime rate regressed on population density

	Dependent variable:
	propertyCrime2016
population_density	0.0004
	(0.004)
Constant	469.292***
	(30.192)
Observations	140
R^2	0.0001
Adjusted R^2	−0.007
Residual Std. Error	218.002 (df = 138)
F Statistic	0.011 (df = 1; 138)
Note:	*p<0.1; **p<0.05; ***p<0.01

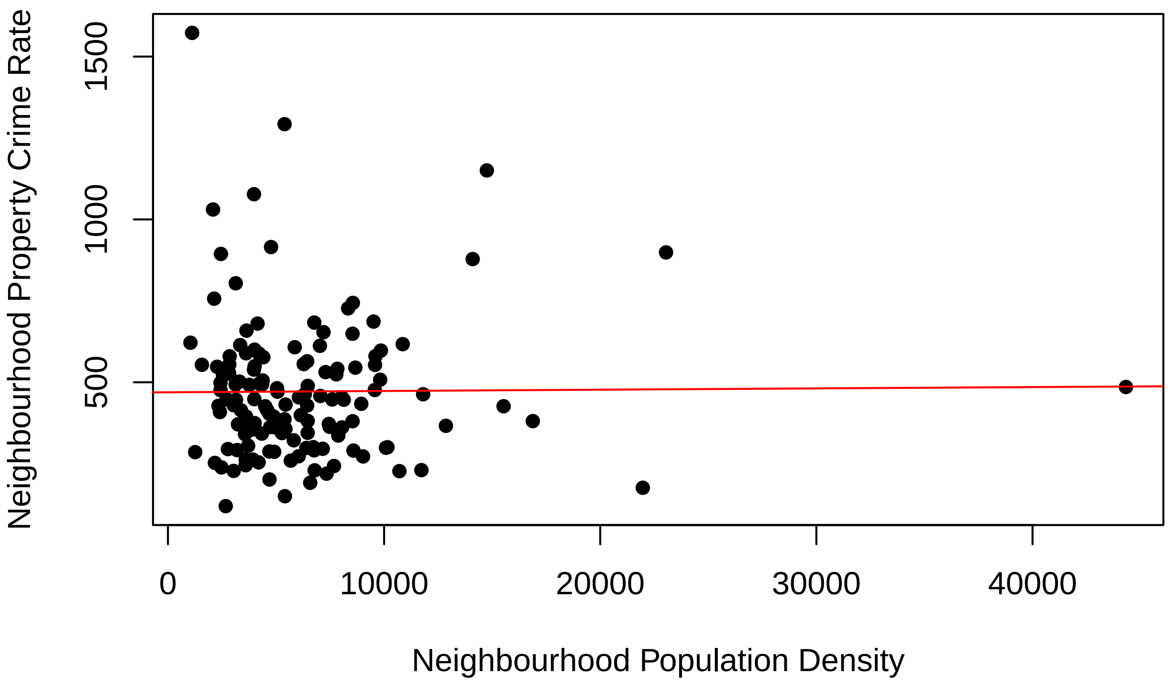

Figure 10: Regression model comparing population density and property crime rates by neighbourhood (2016)

Table 2: Property crime rate regressed on percentage of individuals designated as 'low income'

	Dependent variable:
	propertyCrime2016
low_income_percent	2.307
	(2.379)
Constant	427.491***
	(49.239)
Observations	140
R^2	0.007
Adjusted R^2	−0.0004
Residual Std. Error	217.272 (df = 138)
F Statistic	0.940 (df = 1; 138)
Note:	*p<0.1; **p<0.05; ***p<0.01

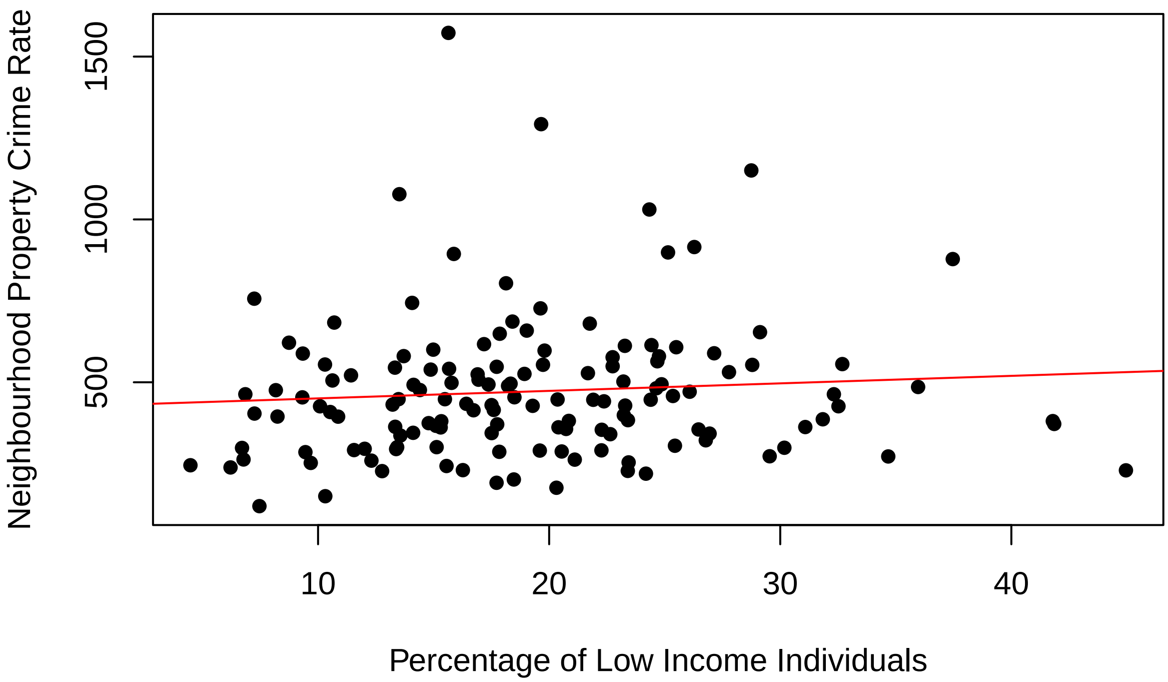

Figure 11: Regression model comparing percentage of low income individuals and property crime rates by neighbourhood (2016)

Table 3: Property crime rate regressed on percentage of individuals who are a visible minority

	Dependent variable:
	propertyCrime2016
total_visible_minority	0.001
	(0.002)
Constant	464.169***
	(28.613)
Observations	140
R^2	0.001
Adjusted R^2	−0.006
Residual Std. Error	217.915 (df = 138)
F Statistic	0.121 (df = 1; 138)
Note:	*p<0.1; **p<0.05; ***p<0.01

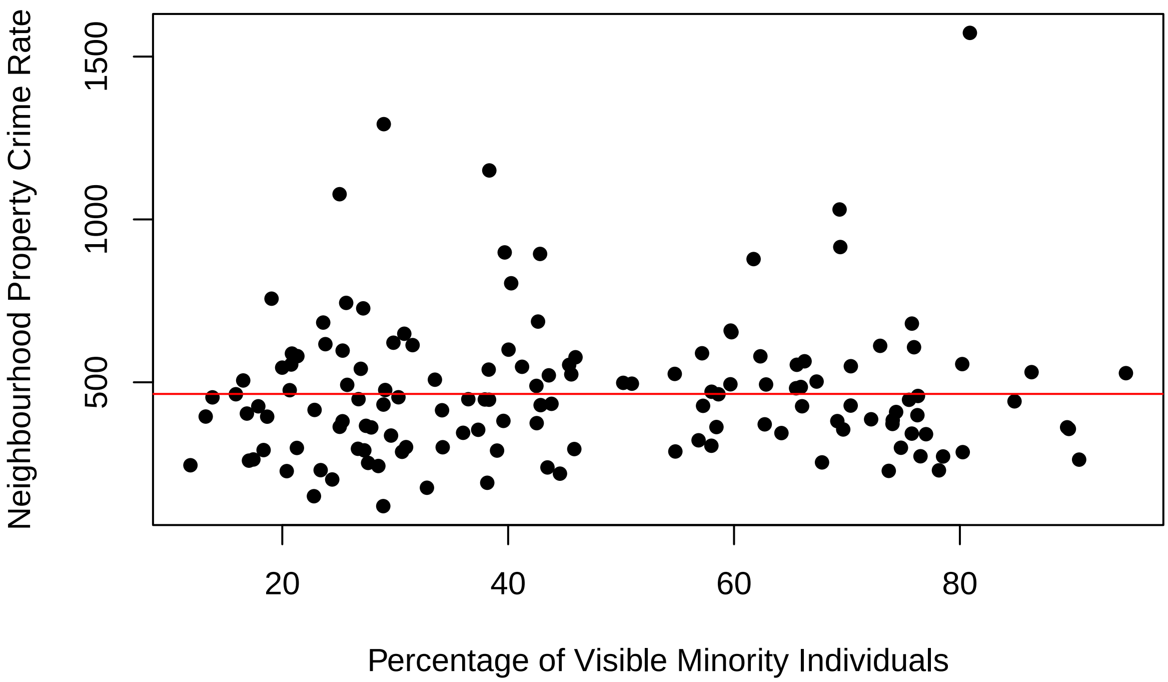

Figure 12: Regression model comparing percentage of visible minority individuals and property crime rates by neighbourhood (2016)

Table 4: Property crime rate regressed on percentage of individuals who are aged 15-29'

	Dependent variable:
	propertyCrime2016
percent_aged_15to29	14.014***
	(3.997)
Constant	188.206**
	(82.790)
Observations	140
R^2	0.082
Adjusted R^2	0.075
Residual Std. Error	208.905 (df = 138)
F Statistic	12.292*** (df = 1; 138)
Note:	*p<0.1; **p<0.05; ***p<0.01

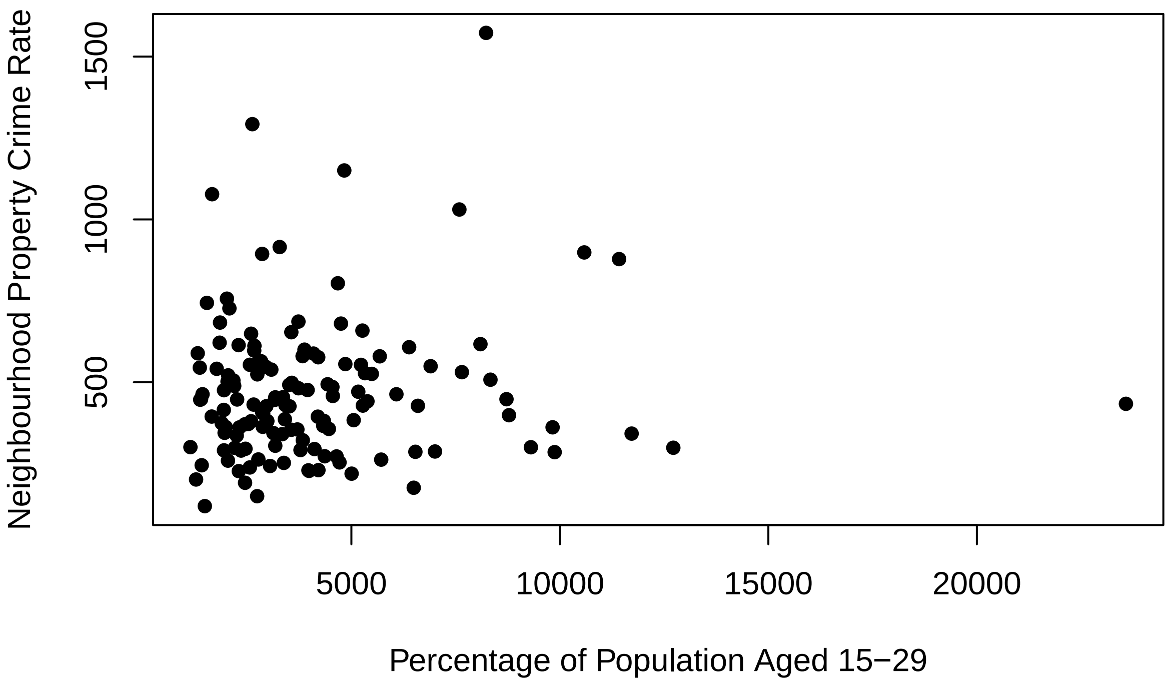

Figure 13: Regression model comparing percentage of young (aged 15-29) individuals and property crime rates by neighbourhood (2016)

Table 1 thorough table 4 summarize the determined regression models of property crime rate against the four social factors of interest, and figure 10 through figure 13 display these regression models in graphical form. These were used to quantify any potential relationship between property crime and select social factors. Table 1 and figure 10 show population density regressed against property crime rate. Table 2 and figure 11 show percentage of low income individuals regressed against property crime rate. Table 3 and figure 12 show percentage of visible minority individuals regressed against property crime rate. Table 4 and figure 13 show percentage of individuals aged 15-29 regressed against property crime rate.

Analysis

Insert Analysis Here

Conclusion

Insert Conclusion Here

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