Investigating the Spatial Patterns of Income Inequality and Crime: Applications of Spatiotemporal Data Analysis Techniques

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Income inequality and crime are two social problems concerning many nations around the world. Such social issues can have detrimental effects on society and are interconnected, meaning that high crime rates may be associated with high levels of income inequality. Spatial data analysis of income inequality and crime can potentially aid in planning inequality reduction and crime prevention measures. A variety of studies have been conducted to explore the spatial patterns of income inequality and crime, but there are still research gaps and uncertainties that exist. First, while income inequality has been analyzed at various spatial scales, there is a lack of research conducted at the small area level within cities and neighbourhoods. Second, while criminology theories such as rational choice theory indicate a positive association between spatial patterns of income inequality and crime, empirical studies have produced inconsistent and sometimes contradictory results. Third, while some studies suggest that the spatial and temporal dimensions of crime are inseparable, research on the spatiotemporal dimensions of crime is limited compared to purely spatial studies. This thesis aims to investigate the spatial variability of income inequality, the relationship between income inequality and crime, and the spatiotemporal variation of crime between business days and non-business days at the small area level. This thesis adopts a manuscript-style format consisting of three papers.

The first paper adopts an exploratory spatial data analysis approach to examine the spatial patterns of income inequality in the City of Toronto at two spatial scales: census tract and dissemination area. Noteworthy locations of within-area income inequality, represented by the Gini coefficient in each area, and across-area income inequality, represented by the median income disparities between different areas, are identified at each spatial scale. This paper also recognizes discrepancies in spatial patterns between the two spatial scales of analysis, since dissemination areas tend to capture more detailed local variation. The issue of scale can be attributed to the modifiable areal unit problem, where different spatial data aggregation units may lead to different statistical results and conclusions.

The second paper applies non-spatial and spatial regression models using frequentist and Bayesian modelling frameworks to explore the impacts of within-area and across-area income inequality on five major crime types in the City of Toronto at the census tract and dissemination area scales. The use of spatial regression models improves the model fit in both frequentist and Bayesian frameworks. The Bayesian shared component model accounts for the interactions between crime types and further enhances model performance. Results obtained from the best-fitting frequentist and Bayesian models are inconsistent but do not conflict in terms of the relationship between crime and income inequality, where within-area income inequality generally increases major crime rates and across-area income inequality has varying effects depending on the crime type and spatial unit of analysis.

The third paper investigates the small-area spatiotemporal variation of five major crime types between business days and non-business days using Bayesian modelling. The study area is Old Toronto, a district of high political and economic activity within the City of Toronto. The results of this paper indicate that non-business days tend to have higher risks of assault and robbery compared to business days, but the overall changes in auto theft, break and enter, and theft over $5,000 are insignificant. For each crime type, the local temporal trends in small areas vary across the study region. Although locations of significant temporal trends are identified for every crime type, crime hot spots generally do not differ between business days and non-business days. Nevertheless, some areas that are considered to be hot spots of assault, robbery or auto theft in both time periods have significantly higher crime risks on non-business days compared to business days. Additionally, sociodemographic characteristics (e.g., low income, residential instability) and built environment factors (parks and business areas) are found to be significantly associated with the spatial patterns of crime, while built environments (schools, parks, and business areas) also explain some local temporal variations of crime.

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List of Abbreviations

AIC	Akaike Information Criterion
BIA	Business Improvement Area
CI	Credible Interval
CT	Census Tract
DA	Dissemination Area
DIC	Deviance Information Criterion
EDA	Exploratory Data Analysis
ESDA	Exploratory Spatial Data Analysis
ICAR	Intrinsic Conditional Autoregressive
LISA	Local Indicators of Spatial Association
LM	Lagrange Multiplier
MAUP	Modifiable Areal Unit Problem
MCMC	Markov Chain Monte Carlo
MTUP	Modifiable Temporal Unit Problem
OLS	Ordinary Least Squares
UGCoP	Uncertain Geographic Context Problem

Chapter 1: Introduction

1.1 Context

Income inequality and crime are two common social issues that nations contend with around the world. Income inequality influences economic development, population health, social trust, education systems, and crime prevention (Dabla-Norris et al., 2015; Kawachi & Kennedy, 1999; Pickett & Wilkinson, 2010). Crime brings physical and psychological injuries to victims and affects individual activities, social connections, and local economies (Robinson & Keithley, 2000; Taylor, 1995). Therefore, it is important to improve our understanding of how inequality and crime occur and interact in urban environments in order to measure, assess, manage, and optimally control for both so we can live in a society that is safe and with a high standard of quality of life.

Income comprises all forms of earnings within a specified time period. Income differences among households are commonly due to discrepancies in salaries or wages, property ownerships, and government transfer payments (Case et al., 2012). Income inequality, which reflects the uneven distribution of income among a population, is a policy challenge in all countries. According to the United Nations (2020), for every country with available data, the richest 10% of the population account for at least 20% of all income, while the poorest 40% account for less than 25% of all income. In Canada, the top 10% received 22.7% of the total after-tax income while the bottom 40% received 21% of the total after-tax income in 2019 (Statistics Canada, 2021).

Crimes are defined as behaviours that break the criminal laws made by the authorities. Crime exists in all societies with formal justice systems, but the prevalence of crime varies significantly across countries possibly due to different definitions of crime as well as diverse cultures, religions, development levels, and natural conditions (Soares, 2004). In 2019, 5,874 police-reported criminal incidents per 100,000 population were recorded in Canada and the crime severity index, which represents both the amount and seriousness of crime, increased for five consecutive years (Statistics Canada, 2020a).

Due to the confidential nature of both income and crime, it can be challenging to obtain data at the individual level with accurate geographic location information attached. Nevertheless, it is common to explore the spatial dimension of income inequality and crime using aggregate data. Income statistics are usually measured over the population residing within a certain geographic region (country, city, etc.). A crime incident is usually reported with a geographic location (street address, geographic coordinates, etc.), while incidents can be aggregated or grouped into geographic areas to obtain crime counts or crime rates. Investigating the spatial patterns of income inequality and crime can help to better understand where and how these two social issues occur and intersect, and aid place-based policymaking.

1.2 Overview of Previous Research

Studies that compare income inequality across geographic areas have been performed at different scales of analysis. Most of these studies quantified income inequality in larger administrative units, such as countries (e.g., Atkinson, 2003), provinces (e.g., Gustafsson & Shi, 2002) and cities (e.g., Glaeser et al., 2009). Limited research has been conducted to investigate and map the spatial patterns of income inequality at finer spatial scales within cities and neighbourhoods. Various indicators of income inequality have been employed in the literature, and the Gini coefficient is the most commonly used metric to quantify income inequality within geographic areas. Additionally, some studies argue that income inequality in small areas is better represented by across-area income disparity (Metz & Burdina, 2018; Wang & Arnold, 2008). A more detailed review of income inequality measures is provided in Section 2.2.1.

With respect to crime, it has been long recognized that crime occurrences are not randomly distributed across space. The heterogeneity of crime counts or crime rates across geographic areas has been explored at various spatial scales, ranging from the country level (e.g., Cole & Gramajo, 2009) to the street segment level (e.g., Groff & Lockwood, 2014). Such research usually includes analysis of crime hot spots (i.e., areas that have higher crime risks) and/or analysis of risk factors for crime (i.e., variables that are associated with crime). In terms of risk factors, research has connected the spatial variability of crime to the diversity of natural and social environments across space. Environmental criminology theories indicate that the spatial patterns of crime are influenced by environmental features that motivate or restrain criminal activities (Wortley & Townsley, 2016). For example, according to social disorganization theory, unfavourable socioeconomic conditions such as high residential instability would worsen social control and hence increase crime risks (Sampson & Groves, 1989). A recent trend in crime research is the use of smaller spatial units of analysis, since smaller areas tend to have more homogenous environmental conditions (Weisburd et al., 2009). Small-area studies also provide precise locations of crime hot spots, which could benefit crime prevention measures.

Income inequality is also considered to be one of the environmental conditions that may either directly or indirectly affect crime. Investigating the relationship between income inequality and crime can strengthen the understanding of crime patterns and potentially improve crime control measures. From a theoretical perspective, high levels of income inequality motivate criminal behaviours through multiple pathways, such as increasing the relative benefits of illegal activities and worsening interpersonal connections and social control (Chiu & Madden, 1998; Hipp, 2007; McCarthy, 2002). Nevertheless, empirical studies of the relationship between income inequality and crime have provided divergent and sometimes conflicting results. For example, Fajnzylber et al. (2002) identified causation from income inequality to violent crime while Neumayer (2005) found the relationship between income inequality and violent crime to be spurious. A more detailed review of environmental criminology theories and the relationship between income inequality and crime, which defines the conceptual framework for crime modelling in this research, is provided in Section 4.2.1.

While spatial analysis of crime contributes to crime control by locating crime hot spots and identifying risk factors, it may overlook the temporal dimension of crime. Crime occurrences are not only clustered around certain locations but also at certain times of the day, week, and year. This is supported by crime opportunity theories, which argue that opportunity is an important cause of crime, and the spatiotemporal distribution of crime opportunities is affected by different human activity patterns across space and time (Felson & Clarke, 1998; see Section 6.2.1 for further details). As a result, spatial crime hot spots of crime may not remain the same in different time periods; for example, outdoor tourist attractions may be associated with high crime risks in the summer peak season but not in the winter off-season. Therefore, the spatial and temporal dimensions of crime should be considered together to better understand where and when to implement crime prevention measures (Andresen & Malleson, 2015). The feasibility of spatiotemporal analysis of crime has improved because of recent advances in the sizes and forms of crime data (Newton & Felson, 2015). Studies have analyzed and mapped the spatiotemporal patterns of crime across years (e.g., Law et al., 2014), seasons (e.g., Quick et al., 2019), days of the week (e.g., Andresen & Malleson, 2015), etc. Nevertheless, the number of spatiotemporal studies in the literature is still limited compared to purely spatial studies and there remains significant potential for applying spatiotemporal analysis of crime for different research purposes.

1.3 Overview of Methodological Approaches

Various methods have been applied for studying the spatial patterns of income inequality and crime. Improvements in such studies rely on developments in spatial data analysis and mapping techniques. The simplest way to present spatially distributed data is to depict data values in each geographic area on thematic maps. More advanced methods account for the special characteristics of spatial data like the associations between spatially neighbouring observations. Exploratory spatial data analysis (ESDA) consists of commonly used methods for exploring and visualizing spatial patterns, which enables locations of significant spatial associations such as local clusters and outliers to be identified (Anselin, 1998; see Section 2.2.2 for further details). For multivariate analysis, such as risk factor analysis for crime, different forms of spatial regression modelling have been widely applied. Such regression modelling approaches include frequentist methods, which consider model parameters as constants, and Bayesian methods, which consider model parameters as random variables (see Section 4.2.2 for further details).

As previously described, it is important to account for the temporal dimension in addition to the spatial dimension of crime. This requires the use of spatiotemporal analysis methods such as space-time cluster detection techniques and Bayesian spatiotemporal modelling (see Section 6.2.2 for further details). Amongst these methods, Bayesian spatiotemporal modelling is particularly advantageous to small-area studies that are subject to the small number problem, where small crime counts lead to unstable parameter estimates (Law et al., 2014). There are various Bayesian spatiotemporal models, and in most models, the spatiotemporal effect in each area can be estimated, which can help with identifying the local crime risk in each area in each time period and assist with implementing crime prevention measures.

As spatial data analysis of income inequality and crime are usually applied to area-based data, the effect of spatial scale on statistical results is unavoidable. This leads to the modifiable areal unit problem (MAUP), which recognizes that data is usually arbitrarily aggregated into geographic units and different data aggregation units may result in different statistical outputs (Fotheringham & Wong, 1991; Openshaw, 1984). There is no standard unit for the spatial analysis of income inequality and crime and in practice, the spatial scales are usually constrained by data sources and availability.

1.4 Research Gaps

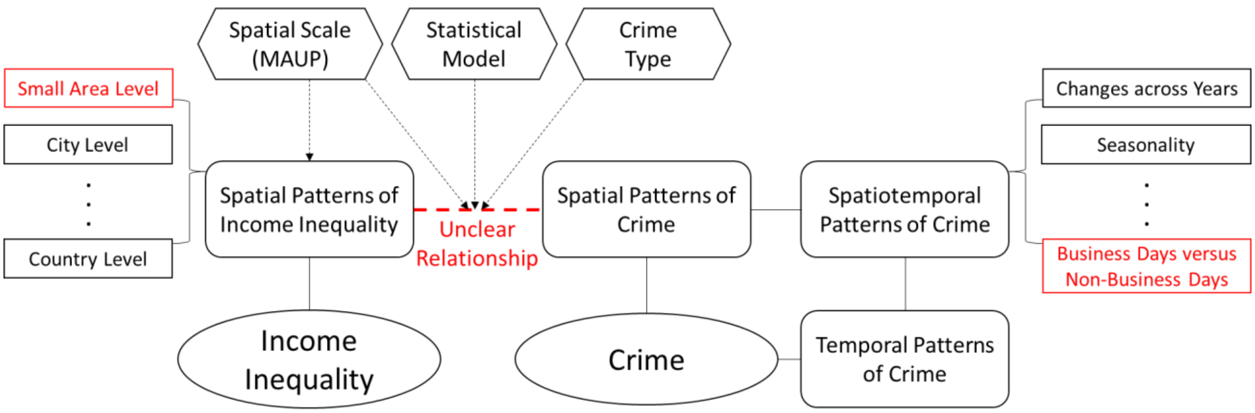


Figure 1-1. Research gaps identified in the literature on the spatial patterns of income inequality and crime (research gaps are marked in red).

Although there are a variety of studies conducted on the spatial patterns of income inequality and crime, several research gaps have been identified in the literature. Figure 1-1 demonstrates three research gaps that this thesis seeks to address. First, while the spatial patterns of income inequality have been explored at various spatial scales, there is a lack of research at the small area level within cities and neighbourhoods. Such research would be useful for locating neighbourhoods that experience high levels of income inequality and highlight areas that require policy interventions, such as tackling accessibility to affordable housing, transportation, and social services. Second, the relationship between income inequality and crime remains unclear and debatable in existing empirical studies. The inconsistent findings from previous studies may be caused by different geographical and methodological contexts, including crime types that were studied, statistical models that were applied, and the spatial scales that were considered. Third, the spatiotemporal analysis of crime is still a relatively new area of research. For example, the small-area spatiotemporal variation of crime between business days and non-business days (weekends and holidays) has not been explored. Understanding the distinctive patterns of how crime varies on weekends and holidays compared to weekdays may be useful for developing proactive policing strategies.

1.5 Research Design, Goals, and Objectives

This thesis adopts a manuscript-style approach consisting of three papers and each paper addresses one of the three research gaps described in Section 1.4. The ultimate goal of this thesis is to contribute to understanding the spatial patterns of income inequality and crime in Toronto, which can potentially aid policymakers in developing measures for improving income inequality and preventing crime at the small area level.

The first paper contributes to understanding the spatial patterns of income inequality at the small area level. The research goal is to identify and visualize the spatial patterns of income inequality in the City of Toronto at the census tract and dissemination area scales. The main objectives of this study are to:

1) Quantify income inequality at the small area level.
2) Explore and map the spatial patterns of income inequality using ESDA tools.
3) Assess the MAUP effects between census tracts and dissemination areas in Toronto.

The second paper contributes to understanding the relationship between income inequality and crime. The research goal is to investigate the impacts of income inequality on crime in the City of Toronto and examine the effects of crime types, statistical models, and spatial scales on the income inequality-crime relationship. The main objectives of this study are to:

1) Quantify within-area and across-area income inequality in each small area.
2) Determine the dependence of five major crime types (assault, robbery, auto theft, break and enter, and theft over $5,000) on income inequality through regression modelling.
3) Employ multiple regression models, including non-spatial and spatial models in the frequentist and Bayesian frameworks, to assess the sensitivity of the income inequality-crime relationship to statistical models.

4) Assess the MAUP effects by adopting two spatial units (census tract and dissemination area) of analysis.

The third paper contributes to understanding the spatiotemporal patterns of crime in the context of weekends and holidays. The research goal is to investigate the small-area spatiotemporal variation of multiple types of crime between business days and non-business days in the Old Toronto area. The main objectives of this study are to:

1) Model the spatiotemporal variation of five major crime types (assault, robbery, auto theft, break and enter, and theft over $5,000) at the dissemination area level using a Bayesian approach.
2) Map the spatiotemporal patterns of each crime type.
3) Assess the spatiotemporal variability of crime based on sociodemographic characteristics and aspects of the built environment.

1.6 Study Area

The study area of the first and second papers is the City of Toronto. The study area of the third paper is Old Toronto, which is a district within the current city limit of Toronto and where significant economic and political activities take place. In order to investigate small-area spatial patterns of income inequality and crime, the two smallest census geographic units, census tract (CT) and dissemination area (DA) are used in this thesis. Detailed definitions of the study area and spatial units of analysis are described in later sections.

Toronto is the largest city in Canada with an area of 630 km^2 and a population of 2.7 million (2016 census). This city has been experiencing increasing crime and income inequality. In 2019, 142,635 criminal code violations were reported to Toronto police, and both the crime counts and crime severity index have been continuously increasing (Statistics Canada, 2020b; Toronto Police Service, 2020a). The Gini coefficient, a commonly used indicator of income inequality, has been worsening in the past few decades in Toronto (Walks et al., 2016). Based on the 2016 census, Toronto has a median after-tax household income of $58,264, and the city-level Gini coefficient is estimated to be 46%. Gini coefficients over 40% are generally viewed as warning signs of income inequality (Kong et al., 2019).

Additionally, income polarization among different zones in Toronto has also been rising. Hulchanski (2010) grouped Toronto neighbourhoods into three "cities" based on the types of changes observed in average income between 1970 and 2005 (adjusted for inflation). The first is in the central core of the city where income levels have been increasing over time. The second is near the northeastern and northwestern edges where income has been decreasing over time. Finally, the third encompasses the rest of the city where income levels have been relatively stable and have not changed significantly. As these three "cities" move apart in trajectory from each other in terms of average income, this results in the middle-income areas within Toronto shrinking over time, whereas the high-income and low-income areas are becoming increasingly prominent (Hulchanski, 2010).

1.7 Data Sources

Datasets obtained from three sources are used in this research. First, the 2016 census, provided by Statistics Canada (2020c), and recorded as polygon data, is used to define the boundaries of CTs and DAs and quantify sociodemographic variables within each CT and DA. There are 572 CTs and 3,702 DAs in the City of Toronto and 1,100 DAs in Old Toronto, yet a few CTs and DAs are excluded in each paper due to data issues (see Sections 2.3, 4.3, and 6.3). Second, crime is quantified based on the major crime indicator data, which is provided by the Toronto Police Service (2020b) and recorded as geocoded points. This research uses occurrences of five types of major crime that fall within the study area between 2015 and 2019, which include 172,821 occurrences within the City of Toronto (assault: 93,817; robbery: 17,814; auto theft: 19,705; break and enter: 35,867; theft over $5,000: 5,618) and 63,725 occurrences within Old Toronto (assault: 36,615; robbery: 6,506; auto theft: 3,920; break and enter: 14,483; theft over $5,000: 2,201). In the third paper, the former municipality boundary data and built environment data (schools, parks, and business areas), obtained from Toronto Open Data (City of Toronto, 2020a, 2020b, 2020c, 2020d), are used to define the boundaries of Old Toronto and quantify built environment characteristics, respectively. Former municipality boundaries, parks, and business areas are recorded as polygons while schools are recorded as points.

1.8 Thesis Structure

This thesis follows a manuscript style, consisting of three manuscript chapters, two connecting chapters, and one concluding chapter. The three manuscripts are written as stand-alone papers, but collectively contribute to understanding the spatial patterns of income inequality and crime, which are important and interconnected policy challenges experienced in most cities. Chapter 2 consists of the first manuscript, which explores the spatial patterns of income inequality in the City of Toronto. The second manuscript in Chapter 4 investigates the income inequality-crime relationship in the City of Toronto. Chapter 6 is the third manuscript, which analyzes the spatiotemporal patterns of crime between business days and non-business days in the Old Toronto area. Chapters 3 and 5 are connecting chapters between the manuscripts, describing the conceptual links between each study. Chapter 7 is a concluding chapter that summarizes the key findings, contributions, and limitations of this thesis and proposes directions for future research.

Chapter 2: Mapping Income Inequality in the City of Toronto Using an Exploratory Spatial Data Analysis Approach

2.1 Introduction

Income inequality, which refers to the uneven distribution of income in a population, is a concerning social problem worldwide. Differing from poverty, which focuses on the low-income population, income inequality is measured over the entire population and it is usually not affected by the average income of the population (Haughton & Khandker, 2009). In other words, income inequality can be a policy challenge in every region regardless of its economic development level. Despite a globally decreasing trend during the past decade, many countries still have high levels of income inequality and the ongoing COVID-19 crisis is exacerbating income inequality (United Nations, 2020).

Research has related income inequality to a wide range of social issues. There is a vast and fast-growing literature on the association between income inequality and population health (e.g., Kawachi & Kennedy, 1999; Pickett & Wilkinson, 2015; Wilkinson & Pickett, 2006). The links between income inequality and other social problems such as crime have also been frequently explored and verified (e.g., Enamorado et al., 2016; Fajnzylber et al., 2002; Kennedy et al., 1998). For scholars who attempt to investigate the effects of income inequality through ecological studies, it is helpful to gain a better understanding of the spatial dimensions of income inequality. For policymakers who seek to address income inequality-related problems within a certain region, it is beneficial to be aware of specific geographic areas that may be problematic and require attention from a policy and resource perspective.

Thematic maps that illustrate the observation at each geographic location have long been used to aid the understanding of spatially distributed data. In addition to the simple depiction of data values, exploratory spatial data analysis (ESDA) provides a series of tools to indicate spatial properties and visualize spatial patterns. ESDA has been widely utilized to analyze different socioeconomic variables, and it can be applied to income inequality mapping and potentially assist decision-making in relevant academic research and policy processes (e.g., Câmara, et al., 2011; Tselios, 2008).

This study aims to examine the use of ESDA in mapping small-area income inequality within a city, which has not been well explored in the literature. Two types of income inequality are considered: income inequality within individual geographic areas, and disparities of income levels among various geographic areas. This study also seeks to investigate a common issue in spatial data analysis and mapping, the modifiable areal unit problem (MAUP), which indicates that different data aggregation units may lead to different statistical results (Openshaw, 1984). Using the data from the City of Toronto, the objectives of this study are, (1) to quantify income inequality and income level in each geographic area, (2) to explore the spatial patterns of within-area and across-area income inequality with ESDA tools, and (3) to assess the MAUP effects by adopting two spatial units of analysis (census tract and dissemination area).

2.2 Background

2.2.1 Measuring Income Inequality

There are various income inequality metrics (the Gini coefficient, the Atkinson index, Theil's measure, etc.), and the Gini coefficient is the most commonly used measure in the literature (Allison, 1978; De Maio, 2007). The Gini coefficient quantifies the deviation of actual income distribution from a completely equal distribution of income in a population. It is an indicator of relative deprivation, which reflects how the relatively poor population lacks resources to maintain high living standards compared to the relatively wealthy population (Townsend, 1979; Yitzhaki, 1979). Theoretically, the Gini coefficient is independent of the spatial scale, the population, and the overall economic status of the study region, thus the measures from different locations or different times can be compared (Ray, 1998).

Despite its popularity, the Gini coefficient is not a flawless metric. Major limitations of the Gini coefficient include its inability to distinguish between different types of income patterns (e.g., income inequality among the lower-income or higher-income population) and its sensitivity to changes in the middle range of the income distribution (Allison, 1978; Cowell, 2011). Although other indicators may compensate for the weakness of the Gini coefficient, it remains debatable whether the choice of indicator would have significant impacts on ecological studies. In the frequently cited study of Kawachi and Kennedy (1997), six income inequality measures, including the Gini coefficient, were all found to be strongly correlated with each other and the choice of measure did not alter the multivariate analysis results. While some subsequent studies have also indicated consistent analysis results with multiple income inequality measures (e.g., Roberts & Willits, 2015; Shi et al., 2003), a few other studies have shown different results, where substantial effects of the choice of indicator were identified (e.g., De Maio et al., 2012; Jorgenson et al., 2017; Weich et al., 2002).

Another issue of income inequality indices is related to the spatial context in which income inequality is perceived. The Gini coefficient and its alternatives only represent income inequality within geographic areas internally. However, in small-area cases within cities, residents may not only be affected by income inequality within their areas of residence, but also influenced by across-area income inequality, especially the income disparities between their areas of residence and the surrounding areas as they can easily gain familiar with and travel to neighbouring areas (Metz & Burdina, 2018; Wang & Arnold, 2008). Therefore, when the spatial unit of analysis is small, it is important to account for across-area income inequality by analyzing the spatial patterns of income levels.

2.2.2 Exploratory Spatial Data Analysis

ESDA is an extension of exploratory data analysis (EDA). EDA provides insights into the data structure using visual methods (e.g., histograms and box plots), but it ignores the unique characteristics of spatial data, such as spatial dependence (Anselin, 1996). ESDA is a series of techniques to depict spatial distributions, identify clusters, outliers, or other forms of spatial associations, and indicate spatial heterogeneity (Anselin, 1998). The core of ESDA is its formal investigation of spatial autocorrelation (Messner et al., 1999). Conventionally, spatial autocorrelation measures the systematic variation in a variable across space, and spatial autocorrelation can be positive, where similar values tend to cluster, or negative, where neighbouring values tend to be dissimilar (Haining, 1990). This is usually represented by a single global statistic, and global Moran's I is a commonly used measure to quantify spatial autocorrelation in the entire study area of interest (Cliff and Ord, 1973).

Since a major objective of spatial data analysis is to identify local spatial patterns (e.g., hot spots and cold spots), the conventional global measures of spatial autocorrelation are inadequate (Anselin, 1995; Messner et al., 1999; Ord & Getis, 2001). A fundamental toolset to discover noteworthy locations of spatial dependency in ESDA is the local indicators of spatial association (LISA). According to Anselin (1995), LISA indicates the level of significant spatial clustering of similar values around each observation in a dataset and a LISA statistic is a function of an observed value and its geographically neighbouring values. For a variable, LISA can be computed at every observed location to decide whether to reject the null hypothesis of spatial randomness, and commonly used LISA statistics include local Moran's I, Local Geary's C and Getis-Ord G/G*(Anselin, 1995; Getis & Ord, 1992).

A more recent advancement in ESDA is the development of multivariate LISA. For example, Anselin (2019) proposes a multivariate extension of local Geary's C, which indicates the distance in multivariate attribute space between an observation and its geographically neighbouring observations. This indicator provides an intuitive way to detect clusters when multiple variables are measured. However, multivariate spatial autocorrelation should be interpreted with caution and the significant clusters identified using the multivariate statistics might not completely comply with the corresponding univariate clusters (Anselin, 2019).

2.3 Study Area and Data Sources

The study area is the City of Toronto, the largest city in Canada. The current boundaries of Toronto were created by amalgamating six former municipalities (Old Toronto, York, East York, North York, Etobicoke, and Scarborough) in 1998. According to the 2016 census of Canada, over 2.7 million people, including a considerable number of immigrants, reside in Toronto (Statistics Canada, 2019). As a city of diverse demographics, Toronto has experienced increasing income inequality and polarization during the past few decades (Walks, 2014). Figure 2-1 shows the boundaries of the study area and the six former municipalities. Former municipality boundaries were obtained from Toronto open data (City of Toronto, 2020a). The six former municipalities are used to describe the locations of interest within this manuscript.

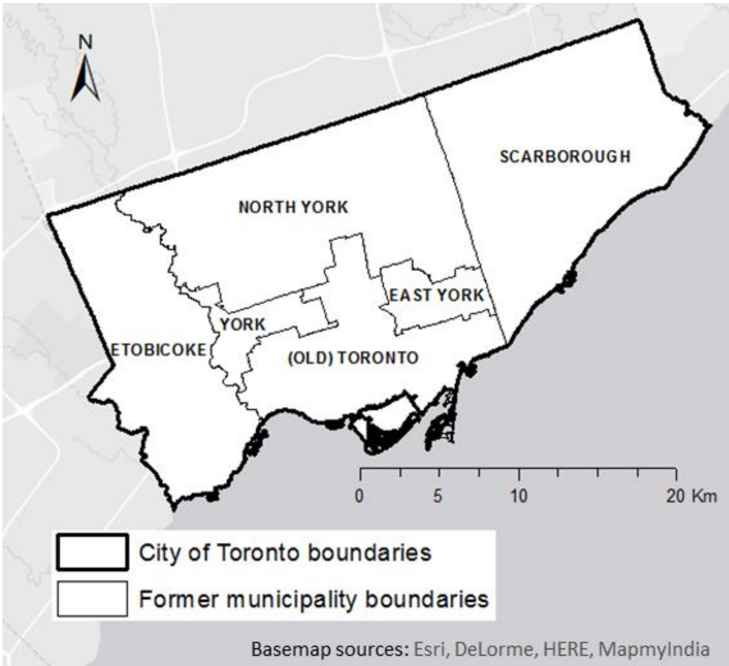


Figure 2-1. The City of Toronto and the six former municipalities within Toronto.

All data used in this study except the former municipality boundary file was extracted from the 2016 census of Canada (Statistics Canada, 2020c). To assess the MAUP effects, this study adopts two census geographic units: census tract (CT) and dissemination area (DA). A CT usually has a population between 2,500 and 8,000 and a DA usually has a population between 400 and 700 (Statistics Canada, 2018a, 2018b). There are 572 CTs and 3,702 DAs in Toronto and all DAs are nested in CTs. 5 CTs and 27 DAs without income data or spatial neighbours (for the purpose of ESDA) are excluded from the entire study. 40 other DAs without complete income data are excluded from the analyses that involve within-DA income inequality. Only 0.4% of the City's population is recorded in these excluded areas and hence the exclusion should not alter the key analysis results. Figure 2-2 shows the CTs and DAs in Toronto and the excluded areas are marked.

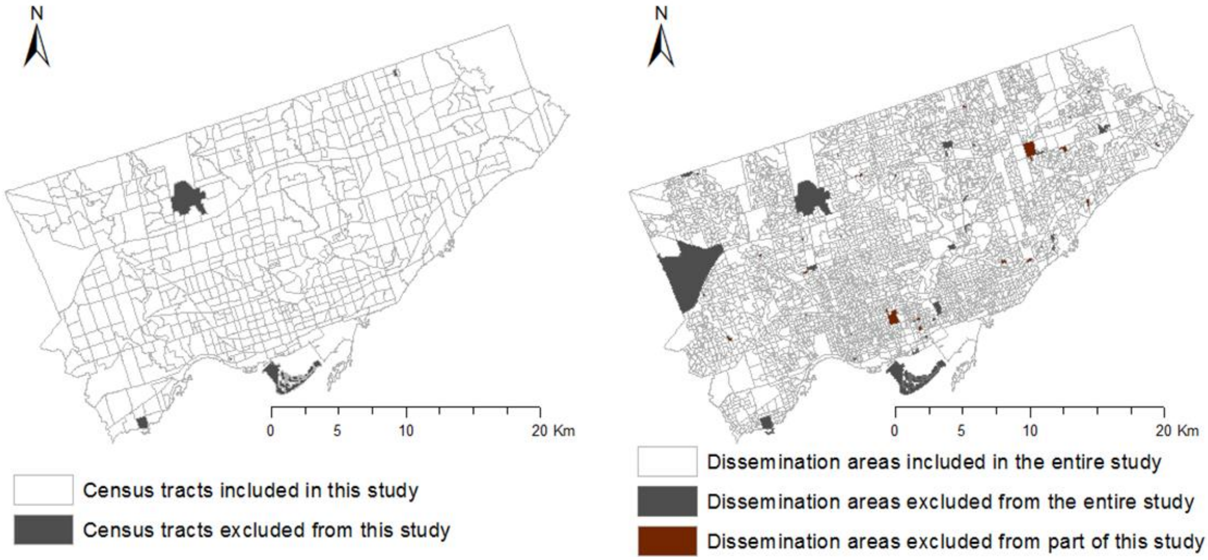


Figure 2-2. Census tracts (left) and dissemination areas (right) in the City of Toronto (areas excluded from this study are marked).

2.4 Methodology

2.4.1 Quantifying Income Levels and Income Inequality

As described in section 2.2.1, residents in small areas may be influenced by within-area and across-area income inequality. This study accounts for both types of income inequality at fine spatial scales. For the analysis of across-area income inequality, the median after-tax household income in each CT and DA was used to represent the local income level. To quantify within-area income inequality, the Gini coefficient was calculated for each CT and DA. This study acknowledges that the Gini coefficient cannot be used to completely assess the income pattern in each area, yet it provides a simple and intuitive way to quantify income inequality for the purpose of spatial analysis. Also, comparing different income inequality indices is beyond the scope of this study, and it is noted that the Gini coefficient is widely used.

While median income data was directly extracted from census datasets, the Gini values were approximated using the after-tax household income categories and the average after-tax household income obtained from the census. The census records the numbers of households in 18 income categories, including an open-ended category at the top (> $150,000), in each CT and DA. To assess the income distribution in each area, each household's income was represented by the midpoint of its income category, and the midpoint of the top open-ended category was inferred based on average income of the area and the estimated cumulated income in the first 17 categories[1]. Using the income distribution, the Gini coefficient was calculated with a Lorenz curve method as illustrated in Figure 2-3. The lower curve indicates the observed relationship between the cumulative proportion of households and the cumulative proportion of income in an area and the upper curve represents an equal income distribution. The Gini coefficient is represented by double the area between the equal distribution curve and the observed curve. The Gini values can range between 0% and 100% and greater values indicate higher levels of income inequality.

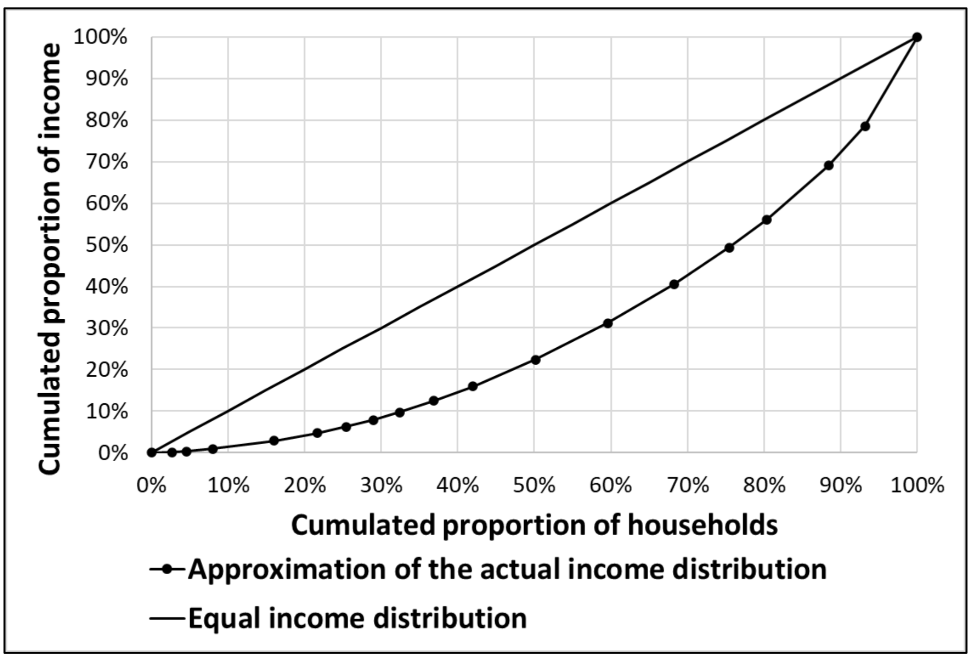


Figure 2-3. A Lorenz curve method to calculate the Gini coefficient.

[1] The midpoint of the top (18th) income category was inferred based on the following function:
$inc_{18} = (INC \cdot \sum_{i=1}^{18} n_i - \sum_{i=1}^{17} n_i inc_i) / n_{18}$,
where inc_i is the income midpoint of income category i; n_i is the number of households in income category i; and INC is the average income of the area.

2.4.2 Spatial Data Analysis

After the quantification process, spatial patterns of the Gini coefficient and median income at each spatial scale were explored. First, the basic data structures were visualized using box maps and box plots, which are primary tools for EDA. The box map and box plot categorize values into four quartiles (<25%, 25-50%, 50-75%, and >100%) and two outlier groups. With the hinge set to 1.5, values greater than the 75th percentile plus 1.5 times the interquartile range and values less than the 25th percentile minus 1.5 times the inter-quartile range are categorized as upper and lower outliers, respectively (the interquartile range is the difference between 25th and 75th percentiles).

Subsequently, univariate ESDA tools, including global Moran's I, local Moran's I and local Geary' C, were applied to each variable at each spatial scale to assess global and local spatial autocorrelation. Global Moran's I is given by Equation 2-1 below:

$$I = \frac{n}{\sum_i (x_i - \bar{x})^2} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i \sum_j w_{ij}}, \tag{2-1}$$

where I is the global Moran's I statistic, ranging from -1 (strongly negative spatial autocorrelation) to 1 (strongly positive spatial autocorrelation); n is the number of areas; x_i or x_j is the observed value at area i or j; $\bar{x}$ is the mean of the variable; and w_{ij} is a spatial weight given by a row-standardized contiguity weight matrix. When area i and j are neighbours, w_{ij} equals one divided by the number of neighbours that area i has, otherwise, w_{ij} equals 0. In this study, neighbours are defined as different areas that share at least one vertex or edge.

Based on Anselin (1995), the two univariate LISA statistics, local Moran's I and local Geary's C, are given by Equation 2-2 and 2-3, respectively:

$$I_i = \frac{x_i - \bar{x}}{S} \sum_{j \neq i} w_{ij} \frac{x_j - \bar{x}}{S}, \tag{2-2}$$

$$C_i = \frac{1}{\sum_i (x_i - \bar{x})^2 / n} \cdot \sum_j w_{ij} (x_i - x_j)^2, \tag{2-3}$$

where I_i and C_i are the local Moran's I statistic and the local Geary's C statistic, respectively in area i; S is the standard deviation of the variable; and x_i, x_j, $\bar{x}$, n, and w_{ij} are the same notion as in Equation 2-1.

In addition to univariate spatial data analysis, multivariate local Geary's C, developed by Anselin (2019) and given by Equation 2-4, was used to explore the bivariate spatial patterns of the Gini coefficient and median income.

$$mC_i = \sum_h \sum_j w_{ij} \left(\frac{x_{hi} - \overline{x_h}}{S_h} - \frac{x_{hj} - \overline{x_h}}{S_h}\right)^2 / k \ , \tag{2-4}$$

where mC_i is the multivariate local Geary statistic in area i; k is the number of variables; x_{hi} or x_{hj} is the observed value of the h_{th} variable in area i or j; $\overline{x_h}$ and S_h are the mean and standard deviation of the h_{th} variable; and w_{ij} is the same notion as in Equation 2-1.

All ESDA indicators were computed using GeoDa, a software package designed for spatial data analysis (Anselin et al., 2010). For each statistic, the significance of spatial autocorrelation was examined using computer permutation tests, which compare the actual result to the distribution of results in randomization processes and provide pseudo p-values of the statistics (Anselin, 1995). Based on the LISA statistics and their corresponding p-values, areas can be categorized into different types of local clusters and outliers (Anselin, 2003). This study applied 9,999 permutations for each statistic and used a p-value of 0.01 to determine significance.

2.5 Results and Discussion

2.5.1 Within-Area Income Inequality: Spatial Patterns of the Gini Coefficient

Descriptive statistics for the Gini coefficient at the two spatial scales are shown in Table 2-1. At the DA scale, the mean is slightly smaller, but the value range and standard deviation are larger. Box maps and box plots of the Gini coefficient at the CT scale and the DA scale are shown in Figure 2-4 and Figure 2-5, respectively. Although the DA scale presents greater variability and local variation, the overall data structures and spatial distributions are not contrasting between the two spatial scales. At both spatial scales, a considerable proportion of higher Gini values, including all upper outliers, are identified in the centre of the city (mostly in Old Toronto and the middle area of North York) while noticeable clusters of lower Gini values are identified in the Scarborough and Etobicoke suburban areas. Global Moran's I statistics indicate significantly positive spatial autocorrelation for the Gini coefficient at both the CT scale (I = 0.537; p = 0.0001) and the DA scale (I = 0.337; p = 0.0001).

Table 2-1. Descriptive statistics for the Gini coefficient

Spatial scale	Mean	Minimum	Maximum	Standard deviation
Census tracts	38.74	25.85	64.13	5.74
Dissemination areas	36.57	10.00	75.73	7.02

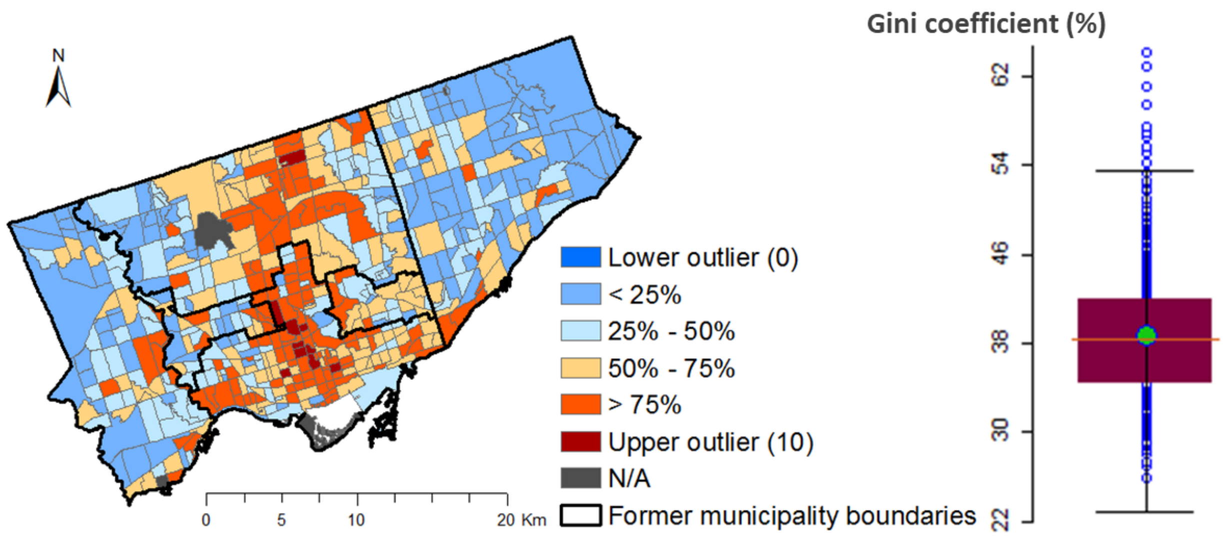


Figure 2-4. Box map and box plot of the Gini coefficient at the CT scale (hinge = 1.5).

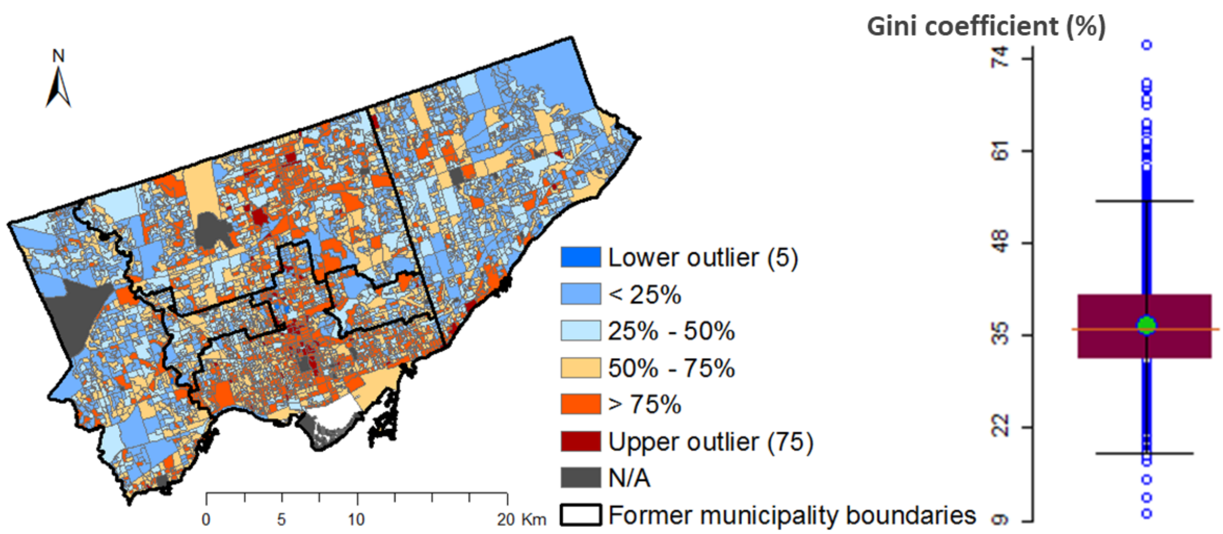
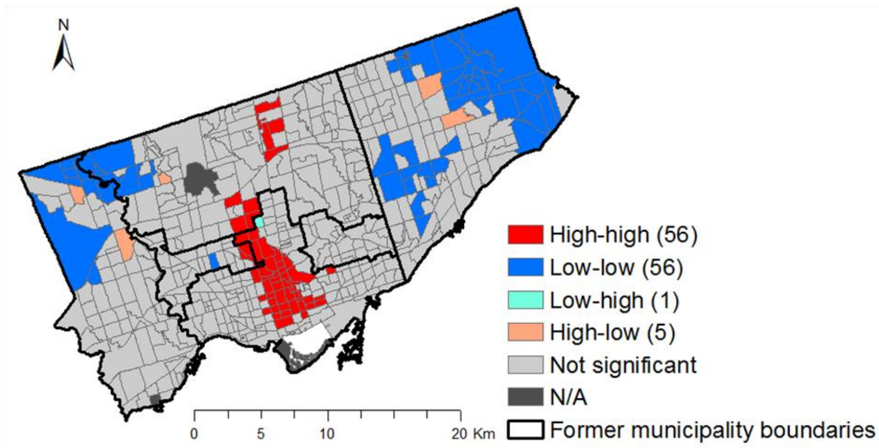


Figure 2-5. Box map and box plot of the Gini coefficient at the DA scale (hinge = 1.5).

Figure 2-6 and Figure 2-7 illustrate the LISA clusters of the Gini coefficient. Note that LISA clusters shown on the maps are only the cluster cores, which means that the surrounding areas of these cores are also part of the clusters. Although some locations are different, the local Moran’s I and local Geary’s C indicate generally similar spatial patterns of high-high and low-low clusters at the CT scale (Figure 2-6). The convergence of such results increases confidence in the identification of where such high-high and low-low clusters are located in the city. Continuous high-high clusters are evident in the centre of the city while continuous low-low clusters are markedly identified in Scarborough and in the northern region of Etobicoke towards the northwestern region of North York. Similar clustering patterns are also identified at the DA scale (Figure 2-7), but some of the cluster cores are comparatively more scattered. In addition, there are some dispersed DA-level cluster cores identified at locations that are not significant at the CT scale; for example, the sporadic low-low cluster cores in the southern region of Etobicoke.

LISA statistics also indicate significant local outliers. Local Moran’s I categorize outlier locations into local low outlier (low-high) and local high outlier (high-low). Local Geary’s C cannot identify outlier types and hence all outliers are marked as negative. While the two spatial scales present similar cluster patterns, some noticeable discrepancies are identified in local outliers. A higher proportion of areas are categorized as local outliers at the DA scale compared to the CT scale. Most of the outlier DAs are not identified within outlier CTs and more interestingly, many outlier DAs are located within CT-level high-high or low-low clusters.

Local Moran's I clusters:



Local Geary's C clusters:

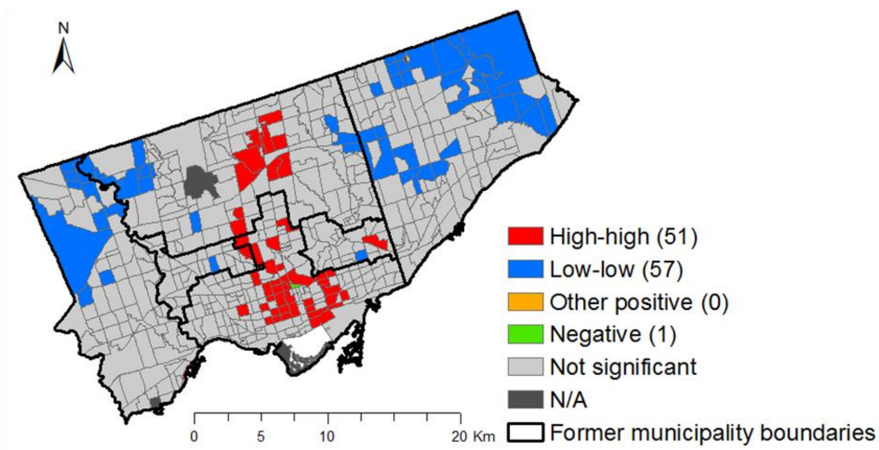


Figure 2-6. LISA cluster maps of the Gini coefficient at the CT scale ($p < 0.01$).

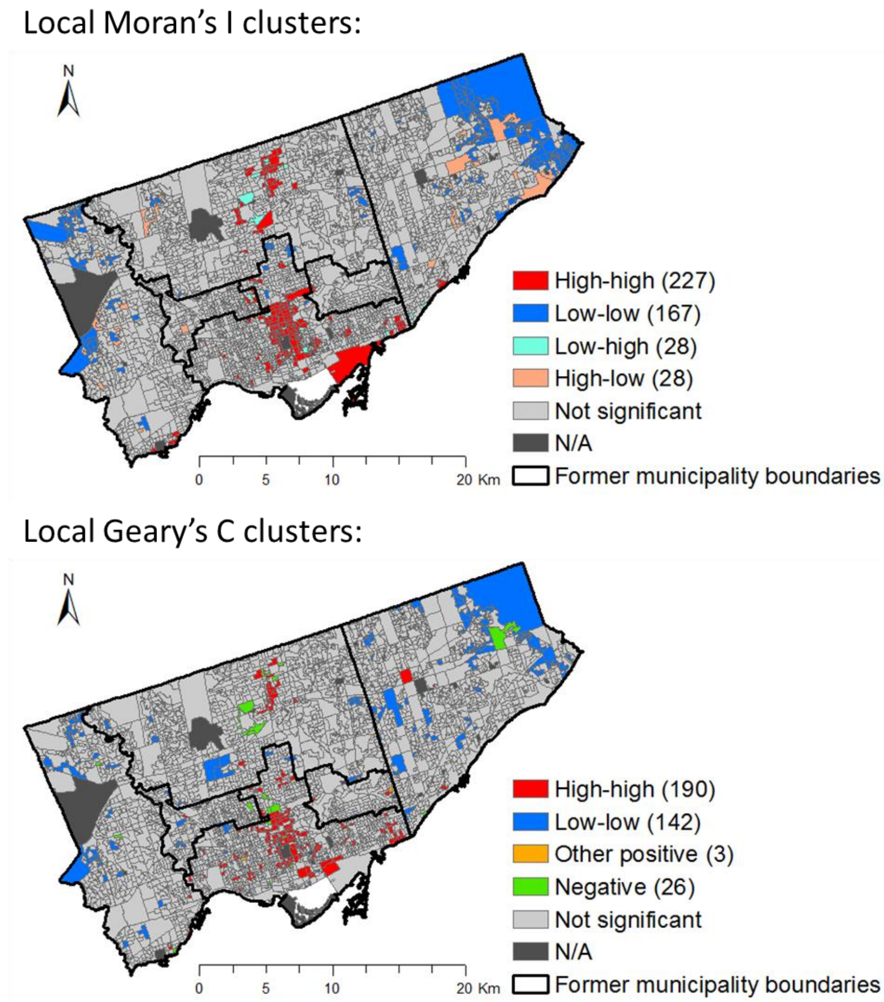


Figure 2-7. LISA cluster maps of the Gini coefficient at the DA scale ($p < 0.01$).

2.5.2 Across-Area Income Inequality: Spatial Patterns of Median Income

Descriptive statistics for median income are shown in Table 2-2. Compared to the CT scale, the DA scale resulted in a larger mean, value range, and standard deviation. Box maps and box plots of median income at the CT scale and the DA scale are shown in Figure 2-8 and Figure 2-9, respectively. Similar to the Gini coefficient, the two spatial scales resulted in similar spatial distributions of median income. At both spatial scales, upper outliers are identified in the central region of the city and the central-southern region of Etobicoke, surrounded by other high neighbouring values. Another noticeable clustering of top-quartile values is located in the eastern region of Scarborough. Lower values also tend to cluster, but the clusters are dispersed across the city. As indicated by global Moran's I statistics, median income also has significantly positive spatial autocorrelation at both the CT scale (I = 0.457; p = 0.0001) and the DA scale (I = 0.565; p = 0.0001).

Table 2-2. Descriptive statistics for median income

Spatial scale	Mean	Minimum	Maximum	Standard deviation
Census tracts	64517.49	21941	206336	23771.41
Dissemination areas	71801.81	12432	422912	32172.20

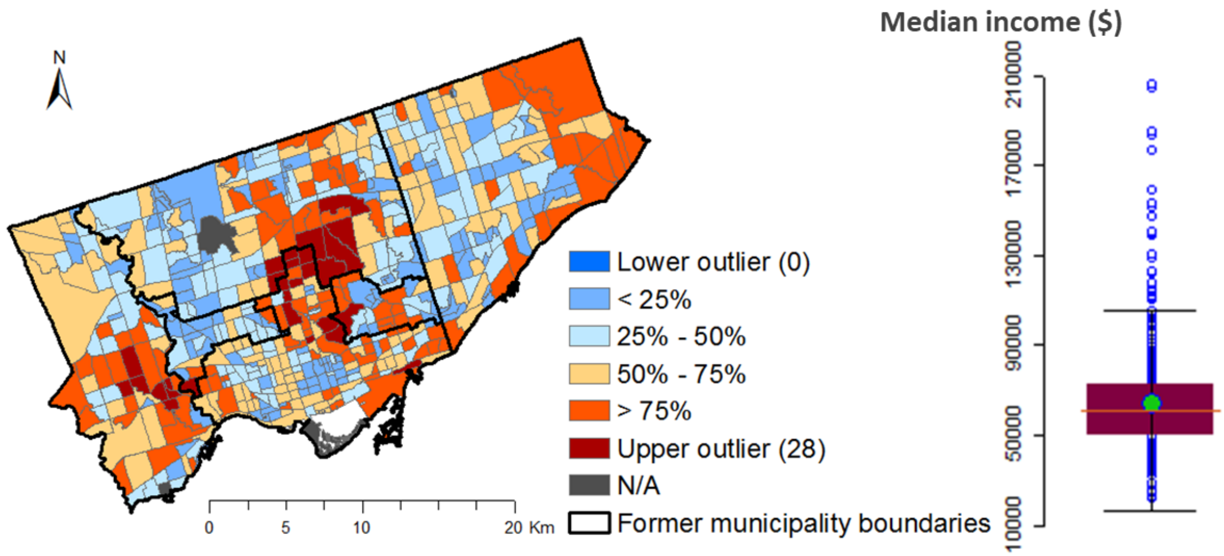


Figure 2-8. Box map and box plot of median income at the CT scale (hinge = 1.5).

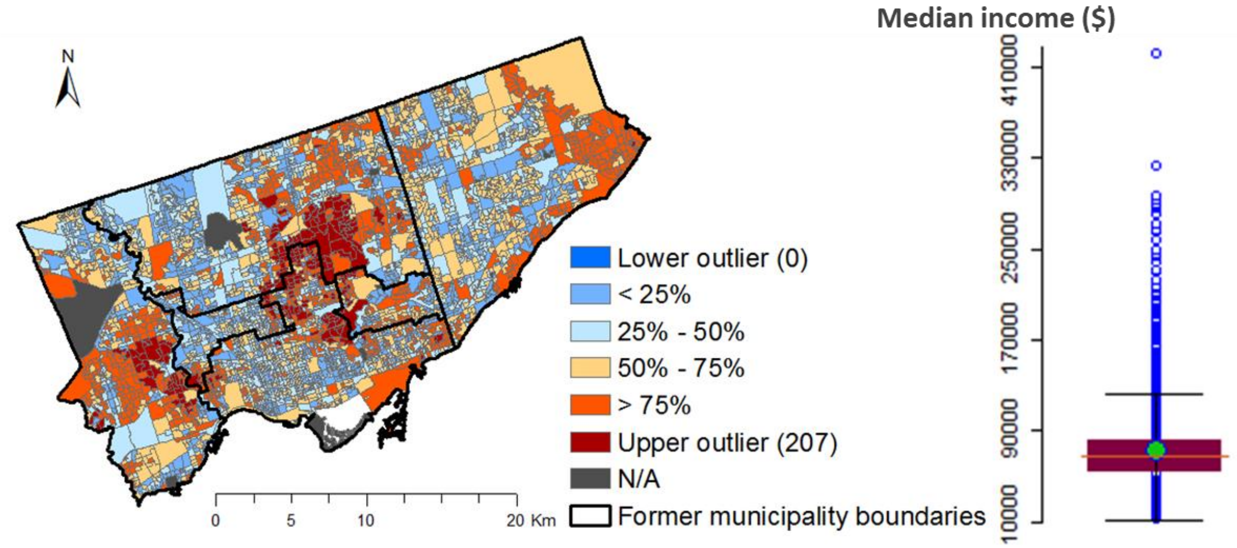
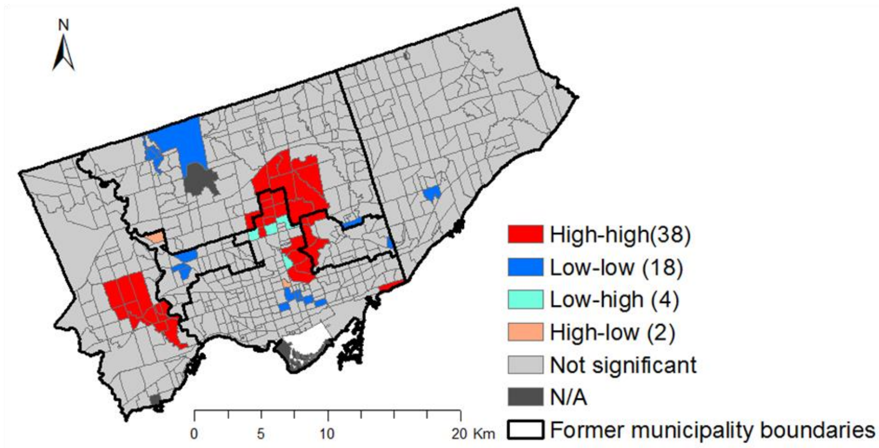


Figure 2-9. Box map and box plot of median income at the DA scale (hinge = 1.5).

According to the CT-level LISA cluster maps (Figure 2-10), local Moran's I indicates noticeable clusters of wealthier areas (high-high) in central-southeastern Etobicoke and in the central region of the city, where Old Toronto, York, East York and North York intersect. Local Geary's C shows additional high-high clusters in eastern Scarborough. Clusters of poorer areas (low-low) indicated by the two LISA statistics at the CT scale are mainly located in the central-western region of the city and the western region of Scarborough. Most of these significant locations remain visible at the DA scale (Figure 2-11) and similar to the Gini coefficient results, the DA scale adds more dispersed clusters. In addition, local Geary's C at the DA scale indicates continuous high-high clusters in the northern region of North York, which are not seen at the CT scale.

Local Moran's I clusters:



Local Geary's C clusters:

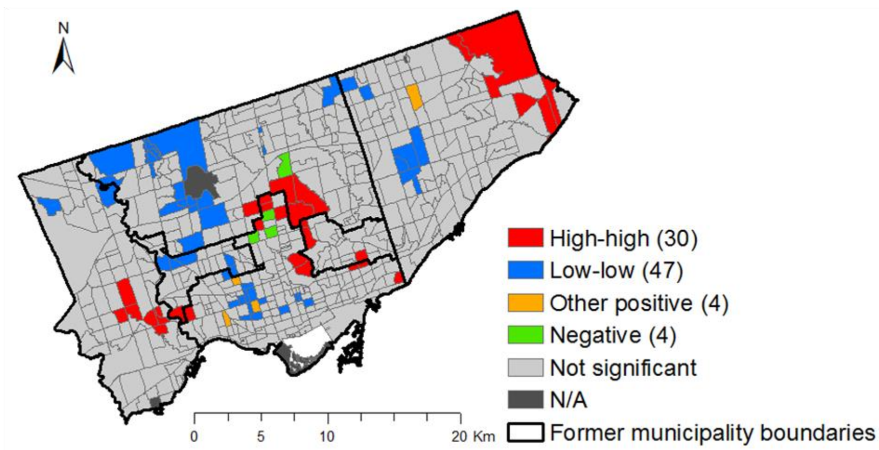


Figure 2-10. LISA cluster maps of median income at the CT scale ($p < 0.01$).

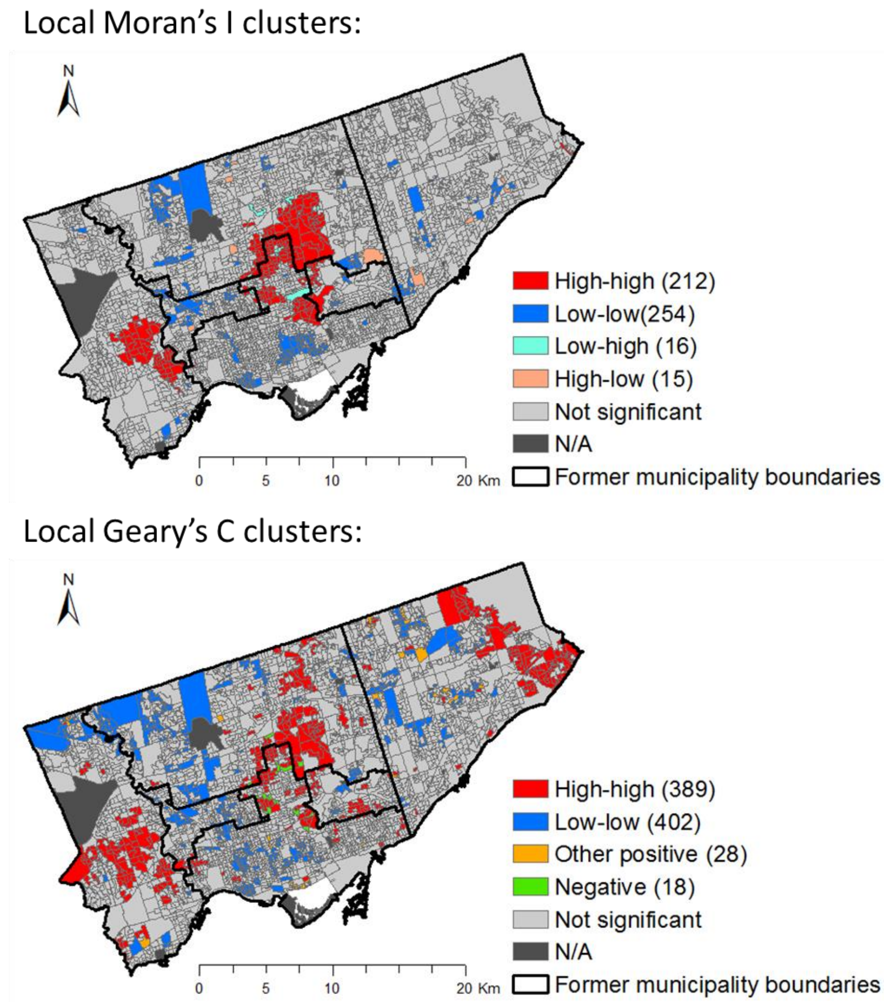


Figure 2-11. LISA cluster maps of median income at the DA scale ($p < 0.01$).

Local outliers of median income, which can be viewed as across-area income inequality hot spots, are of particular interest. At the CT scale, local Moran's I statistics identified four low outliers near the high-high clusters in the central region of the city and two high outliers near the low-low clusters in Old Toronto and York. Residents in the low outlier CTs and residents in the surrounding CTs of high outlier CTs might perceive more across-CT income inequality, since the neighbouring CTs have significantly higher income levels. Local Geary's C indicates four negative cluster cores at the CT scale in the middle of the city and two of the negative cluster cores are marked as low outliers in the local Moran's I results. The other two CTs have median incomes in the top quartile and are categorized as high-high cluster cores in the local Moran's I results. However, their median incomes are still relatively low compared to their surrounding CTs.

At the DA scale, local Moran's I identified 16 low outliers and local Geary's C identified 18 negative cluster cores. Similar to the CT scale, some of the local Geary's C negative cluster cores overlap with the local Moran's I low outliers and the remainder are CTs with median incomes that are higher than the average but lower than their surrounding CTs. All of these local low outliers are identified around the high-high clusters in the central region of the city, which shows similar patterns as the CT scale. Nevertheless, most of them do not fall within the local outlier CTs, which implies that the two spatial scales captured different locations of significant local across-area income inequality. As for the 15 local Moran's I high outliers at the DA scale, they are dispersed across the city and none of them were found within the two high outlier CTs. Similar to the Gini coefficient, some of the outlier DAs for median income are found within the high-high or low-low clusters at the CT scale.

2.5.3 Bivariate Spatial Patterns of the Gini Coefficient and Median Income

In theory, within-area income inequality, represented by the Gini coefficient, is independent of the income level, represented by median income (Ray, 1998). However, the Pearson correlation coefficient indicates a negative correlation between the Gini coefficient and median income in this study area. The negative correlation is not significant at the CT scale (Pearson coefficient = -0.08; p = 0.07) but strongly significant at the DA scale (Pearson coefficient = -0.29; p = 0.00). In other words, in Toronto, DAs with higher income levels also tend to have more equal income distributions. Bivariate local Geary's C cluster maps shown in Figure 2-12 and Figure 2-13 provide more insights visually into the interactions between the two income variables.

Bivariate local Geary's C results consider both the Gini coefficient and median income, while indicating the locations of significantly positive and negative clusters. Cross-classification was further applied to the positive cluster cores based on their values and spatial lags (the spatial lag of a value is the average value of its geographic neighbours). The classification scheme is shown in Table 2-3 and positive cluster cores that do not fall in any categories are marked as "other positive".

Table 2-3. Cross-classification scheme for the bivariate Geary's C positive cluster cores

Gini coefficient	**Spatial lag of the Gini coefficient**	**Median income**	**Spatial lag of the Median income**	**Category**
Below average	Below average	Above average	Above average	Low-low/high-high
Below average	Below average	Below average	Below average	Low-low/low-low
Above average	Above average	Above average	Above average	High-high/high-high
Above average	Above average	Below average	Below average	High-high/low-low

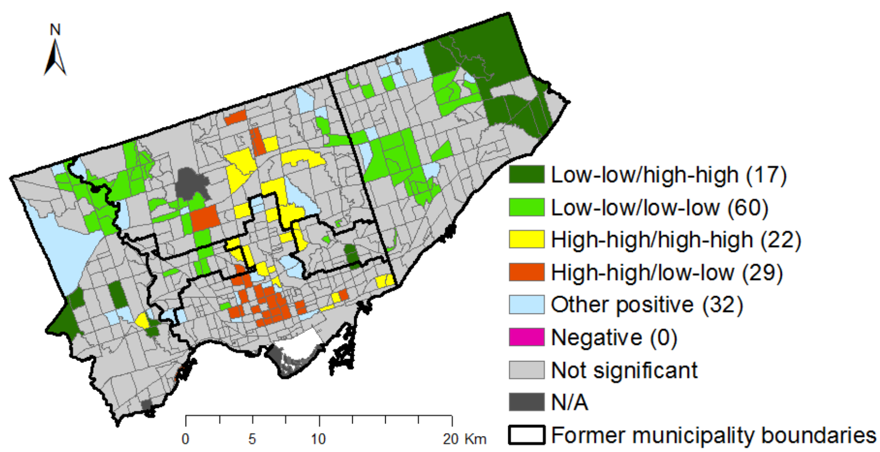


Figure 2-12. Bivariate local Geary's Cluster maps for the Gini coefficient and median income at the CT scale (cross-classification is applied to positive cluster cores).

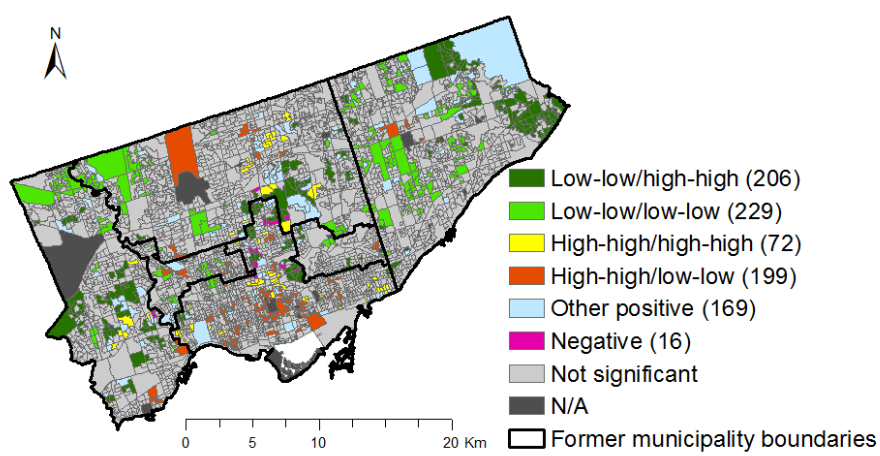


Figure 2-13. Bivariate local Geary's Cluster maps for the Gini coefficient and median income at the DA scale (cross-classification is applied to positive cluster cores).

At both spatial scales, there are noticeable clusters of lower Gini coefficients and higher median incomes (low-low/high-high) in eastern Scarborough and central-southern Etobicoke. At the DA scale, low-low/high-high clusters are also identified in the centre of the city. These clusters of higher income levels and more equal income distributions can be viewed as zones with the "most desirable" income profiles in Toronto. Conversely, the "worst" income profiles (i.e., high-high/low-low) are mainly found in Old Toronto and North York at both spatial scales, and at the DA scale, more dispersed high-high/low-low clusters are identified in other former municipalities. Areas with lower income levels but more equal income distributions (low-low/low-low) are markedly identified in the northwestern region of the city and western Scarborough. Areas with higher income levels but less equal income distributions (high-high/high-high) are mainly located in the central region of the city. However, some of the CT-level high-high/high-high clustering areas become part of the low-low/high-high clusters at the DA scale. Compared to the CT scale, a higher proportion of the positive cluster cores at the DA scale are categorized as low-low/high-high or high-high/low-low, which is consistent with the bivariate correlation results that indicate a more significant negative correlation between the Gini coefficient and median income at the DA scale. Another discrepancy between spatial scales is about local outliers. No bivariate local outliers are identified at the CT scale, but 16 bivariate local outliers are identified at the DA scale. 15 of the outlier DAs are in the central core of the city and overlap with some of the univariate local Geary's C outlier DAs.

2.5.4 Income Inequality and the Modifiable Areal Unit Problem

The EDA and ESDA results show some clear discrepancies between spatial scales or boundary units of analysis. Overall, the DA scale results in greater variability for each variable and captures more detailed local spatial patterns in both univariate and bivariate tests. This is consistent with previous studies about the MAUP, which recognized that larger spatial data aggregation units tend to mask variation within the unit and conceal local extremes that occur at finer spatial scales (e.g., Fotheringham & Wong, 1991; Openshaw, 1984; Prouse et al., 2014). Figure 2-14 illustrates how the CT scale masks DA-level local outliers of median income with two examples. CT-A has median income in the upper outlier group and is categorized as a LISA high-

high cluster core. However, this CT-level measure overlooks a DA with median income in the bottom quartile that is categorized as a LISA low outlier. On the contrary, CT-B is a bottom-quartile CT that is categorized as a LISA low-low cluster core, while it includes a top-quartile DA that is categorized as a LISA high outlier.

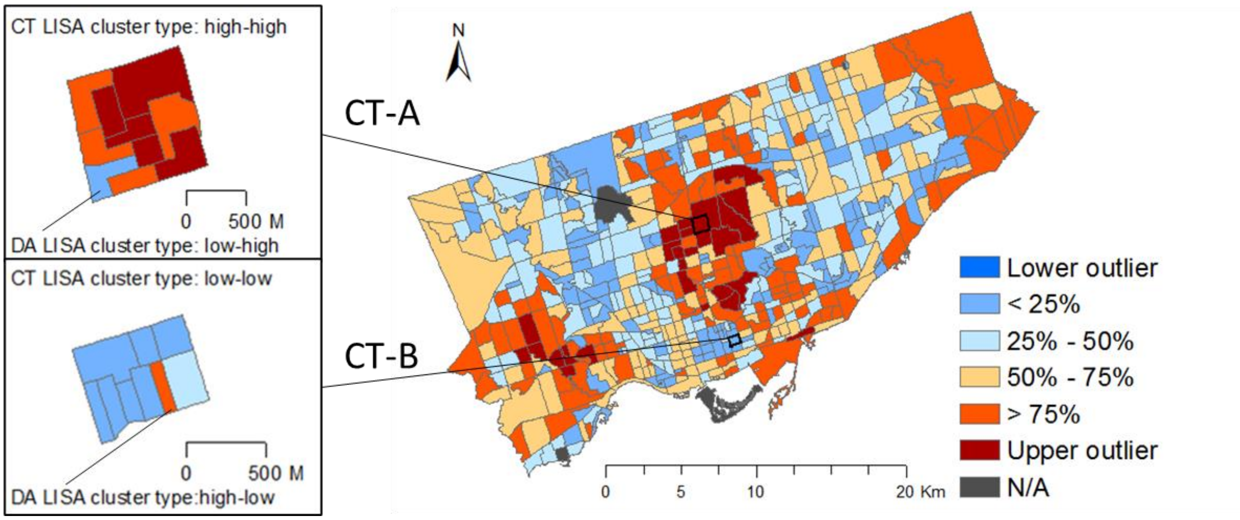


Figure 2-14. Examples of the MAUP effects on median income. The main map shows the median income at the CT scale; the inset maps show the median income at the DA scale. The legend applies to every map.

Similar to the median income, some CT-level Gini values might mask DA-level outliers (e.g., CT-C in Figure 2-15). However, the MAUP effects of the Gini coefficient are more complex than that of median income; some discrepancies cannot be explained by the generalization effects of the larger areal unit. For example, CT-D in Figure 2-15 records a Gini coefficient of 45.5, which falls in the top quartile. Within this CT, 5 out of the 8 DAs have Gini values in the bottom half and only one DA has a top-quartile Gini value (44.0), which is still lower than the CT-level measure. This difference between spatial scales might be caused by the transformation between across-area and within-area income inequality. As shown in the map, although these DAs have relatively equal within-DA income distributions, there are clear income disparities between the western and eastern DAs. When the households from these DAs are combined into one income distribution, the across-

DA income disparities become part of the within-CT income inequality, thus resulting in a CT-level Gini value that is higher than any of the DA-level Gini values.

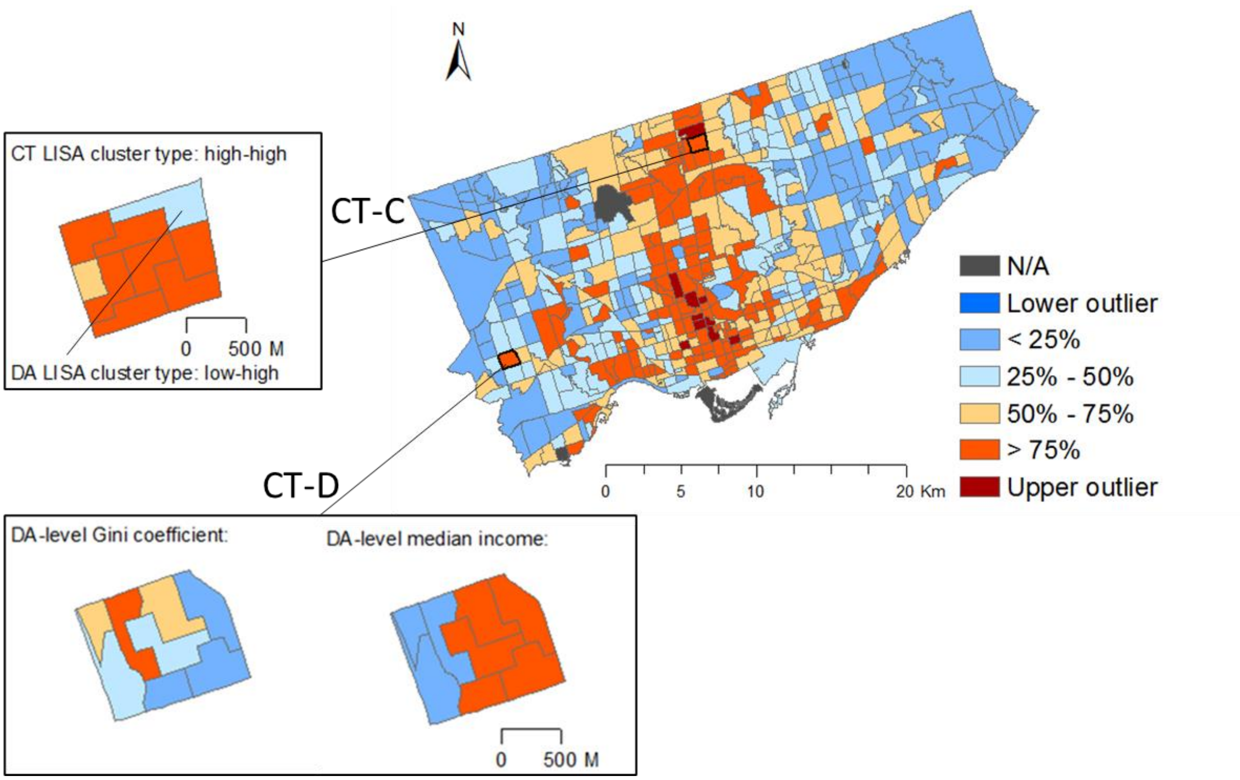


Figure 2-15. Examples of the MAUP effects on the Gini coefficient. The main map shows the Gini coefficient at the CT scale; the inset map for CT-C and the left part of the inset map for CT-D show the Gini coefficient at the DA scale; the right part of the inset map for CT-D shows the median income at the DA scale. The legend applies to every map.

When computing socioeconomic statistics, smaller areal units are usually considered preferred because they contain less variation (Prouse et al., 2014). Theoretically, a smaller area tends to have a more homogeneous population, thus the residents can be better represented by the socioeconomic statistics. In this study, although the Gini coefficient has a higher extremity at the DA scale, the mean is slightly lower, indicating that within-DA income distributions tend to be more equal than within-CT income distributions. Therefore, residents can be better represented by DA-level income statistics, such as median income. Moreover, in spatial data analysis, the DA scale can capture more detailed spatial patterns, especially for the local outliers that are masked at the CT scale.

Despite its advantages, the CT scale is not necessarily better than the DA scale in the spatial analysis of income inequality. For both the Gini coefficient and median income, the CT scale presents more clear/distinct depictions of the spatial patterns with more continuous clusters, thus areas that require particular attention can be easily recognized and detected. Therefore, the CT scale would be a more appropriate spatial unit for the purpose of larger-area or regional policymaking. In terms of local across-area income inequality, the DA scale captures many local outliers of median income that are masked by CT-level clusters. However, it does not necessarily mean that such DA-level local outliers more accurately represent across-area income inequality hot spots compared to the CT-level local outliers. In reality, there may be a high degree of mobility and residents may be knowledgeable about areas outside their neighbouring DAs, and it is difficult to tell whether the income disparities between nearby CTs or DAs have more significant influence than shown in spatial analysis results based on aggregate data alone. This issue also applies to the Gini coefficient as it is difficult to define the geographic context in which within-area income inequality is perceived. Moreover, different residents of the same area can perceive income inequality in different geographic contexts due to various daily activity patterns. This reflects the uncertain geographic context problem (UGCoP), which recognizes the deviation of the areal unit in which the variables are measured from the true individual geographic context (Kwan, 2012). Therefore, when analyzing income inequality and its impacts, spatial scales should be selected based on the contexts of research or policymaking and applied with caution. Also, it would be helpful to conduct a sensitivity analysis that compares the spatial patterns of income inequality at different spatial scales to determine the impacts of spatial units and how boundaries of such units are defined.

2.5.5 Limitations and Future Directions

Several limitations of this study are worth mentioning. First, constrained by the census data, the Gini coefficients used in this study were only approximated, thus they are inevitably inaccurate. Future research could use other data sources or try different within-area income inequality measures and test whether the small-area spatial patterns of within-area income inequality are sensitive to quantification methods. Second, the ESDA results of median income provide an intuitive way to explore overall and local across-area income inequality, but for future research, especially in multivariate analysis, it would be useful to quantify and further investigate across-area income inequality. Some methods to quantify income disparities between neighbouring areas can be found in the literature and could be tested in the future (Metz & Burdina, 2018; Wang & Arnold, 2008).

As for the assessment of the MAUP effects, this study only tested two spatial scales and due to the use of census data, both were census geographic units. Future work could test more spatial units, especially non-census units if alternative datasets are available, to further examine the sensitivity of the spatial patterns of income inequality to spatial scales. In addition, research on subjective perceptions of income inequality may help to determine an appropriate spatial scale at which to quantify income inequality. Future research could use surveys to initially investigate perceived income inequality and then to subsequently compare these results to patterns of income inequality derived at different spatial scales to identify the appropriate spatial unit at which income inequality would be best represented.

2.6 Conclusions

This study has demonstrated the use of ESDA techniques in income inequality mapping in the City of Toronto at two small spatial units of analysis. Spatial patterns of within-area and across-area income inequality were assessed using univariate LISA cluster maps of the Gini coefficient and median income. Multivariate Geary's C, an extension of univariate LISA, was applied to mapping the interactions between the Gini coefficient and median income. This study also identified some discrepancies in the results at the CT scale versus the DA scale, which could be attributed to the MAUP effects. Although the CT scale and the DA scale have some similarities in terms of the data structures and spatial patterns of the Gini coefficient and median income, the DA scale captures greater variability and more detailed local variation. This scale issue could have significant impacts on the interpretations of income inequality. For example, the locations of across-area income inequality hot spots, represented by local outliers of the median income, are very different at the two spatial scales. These findings imply that it is important to consider the MAUP effects and to explore the use of different spatial units when investigating income inequality at the small area level.

Results from this study indicate some noteworthy locations of income inequality in Toronto at the two spatial scales. For example, the centre of the city (from Old Toronto to North York) experiences more severe within-CT and within-DA income inequality. Within this zone, the centre of Old Toronto is particularly interesting and characterized by clusters of lower income levels, evidently an area where income inequality is problematic from a planning perspective. For overall across-area income inequality, it is noted that western Scarborough and the central-western region of the city have lower income levels when compared to the rest of the city. In terms of local across-area income inequality hot spots, this study identifies multiple CTs and DAs with significantly lower income levels compared to the surrounding areas. The majority of these areas were found to be in close proximity to the higher-income clusters located in the centre of the city. There are also CTs and DAs with significantly higher income levels than the surrounding areas dispersed across the city. To better address social problems related to income inequality and to improve equality measures and distribution of resources and access to services across Toronto, the aforementioned zones would require greater attention from a policy and urban planning perspective.

Chapter 3: From the Spatial Variability of Income Inequality to the Spatial Variability of Crime

The first manuscript (Chapter 2) explores the spatial patterns of income inequality in the City of Toronto at the small area levels. At both the census tract and dissemination area scales, the results demonstrate the variations of the income levels and income distributions from area to area and identify areas that experience relatively severe income inequality. These results are important to scholars and policymakers who seek to address social issues because the spatial variability of income inequality is closely associated with the spatial variability of various social problems (population health, crime, education, etc.).

The social problem investigated in the following two manuscripts is crime, which is considered to be a direct threat to public safety. It is commonly known that crime incidents are not randomly distributed over space and crime rates vary across geographic areas. The next manuscript (Chapter 4) connects the spatial variability of income inequality to the spatial variability of crime. Guided by environmental criminology theories, the second manuscript aims to model the spatial patterns of crime and assess the relationship between income inequality and crime at the census tract and dissemination area scales in the City of Toronto. Furthermore, as the results of the first manuscript suggest that the spatial patterns of income inequality are sensitive to the spatial units of analysis, the second manuscript extends this analysis to the income inequality-crime relationship.

Chapter 4: Exploring the Relationship between Income Inequality and Major Crimes in the City of Toronto Using Frequentist and Bayesian Modelling Approaches

4.1 Introduction

Income inequality, which refers to the uneven distribution of income in a population, is a global concern, especially in urban cores and areas of high population density. Although income inequality has generally declined during the past decade, it remains at high levels in many countries, and the ongoing COVID-19 pandemic is widening the income gap between the rich and the poor (United Nations, 2020). Research has identified the detrimental effects of income inequality on many dimensions of society, including population health, economic growth, education systems, social trust, and crime control (Dabla-Norris et al., 2015; Kawachi & Kennedy, 1999; Pickett, & Wilkinson, 2010). Among these social issues, studying crime as a direct threat to public safety is of particular interest. The links between income inequality and crime are supported by multiple criminology theories. For example, rational choice theory indicates that income inequality increases the relative benefits of illegal activities compared to legal activities and hence motivates the poorer population to commit crimes (Cornish & Clarke, 1986). As crime occurrences are usually not randomly distributed across space, research on the income inequality-crime relationship can aid the understanding of crime patterns and strengthen crime prediction and prevention.

Empirical studies about the income inequality-crime relationship have been conducted in different regions around the world and divergent results have been reported. Many studies have demonstrated a positive association between income inequality and crime (e.g., Enamorado et al., 2016; Fajnzylber et al., 2002; Kennedy et al., 1998). On the contrary, some studies demonstrated that the effects of income inequality on crime are insignificant, spurious, or negative (e.g., Allen, 1996; Kang, 2016; Neumayer, 2005). The inconsistencies in previous empirical study results are likely driven by different research contexts. First, analyses of different crime types may produce different outcomes, which is supported by studies that have explored the relationships between multiple types of crime and income inequality. For example, Kelly (2000) found income inequality positively associated with violent crime but not associated with property crime. Choe (2008) analyzed the impacts of income inequality on seven crime types and significant impacts were only identified with burglary and robbery.

Second, the choice of statistical modelling approaches affects the analysis results and conclusions. Some studies applied bivariate correlation indexes for assessing the association between income inequality and crime (e.g., Pickett et al., 2005). More studies have employed multivariate regression models and emphasized the importance of including other risk factors for crime to produce unbiased results (e.g., Neumayer, 2005). Some studies also indicate the necessity of using spatial regression models to deal with the spatial autocorrelation problem in crime data (e.g., Scorzafave & Soares, 2009). In more recent crime research, Bayesian modelling has become popular and it offers various advantages compared to the traditional frequentist approaches, such as the incorporation of prior knowledge (e.g., Law et al., 2014). Nevertheless, Bayesian methods have not been widely applied to the analysis of the income inequality-crime relationship.

Finally, the spatial scales at which crime and income inequality are quantified might influence the analysis results as well. This issue of spatial scale is known as the modifiable areal unit problem (MAUP), which recognizes that data is usually arbitrarily aggregated in geographic studies and different data aggregation units may lead to different parameter estimates in multivariate analysis (Fotheringham & Wong, 1991; Openshaw, 1984). Although many spatial units, ranging from the country scale to the smallest census scale, have been adopted in previous studies of the income inequality-crime relationship, limited research has examined the MAUP effects by analyzing multiple spatial scales. Furthermore, some studies suggest that when smaller spatial units are used, income inequality may be better captured by across-area measures that quantify the income differences between neighbouring areas than traditional within-area measures that represent the income distribution in each individual area (Metz & Burdina, 2018; Wang & Arnold, 2008).

By recognizing the gaps and uncertainties in the literature, this study aims to contribute to better understanding the income inequality-crime relationship based on various crime types, statistical modelling approaches, and spatial scales via empirical analyses based on data from the City of Toronto. Non-spatial and spatial regression models based on frequentist and Bayesian approaches are applied to quantify the impacts of within-area and across-area income inequality on the rates of five major crimes (assault, robbery, auto theft, break and enter, and theft over $5,000) at the census tract and dissemination area levels. Results from different models and different spatial scales are compared in this research. By examining the associations between income inequality and five major types of crime, this study also seeks to strengthen the understanding of spatial crime patterns within Toronto neighbourhoods, which will potentially aid in informing local crime prevention and control practices.

4.2 Background

4.2.1 Theoretical Links between Income Inequality and Crime

Studies of crime patterns have been guided by various environmental criminology theories which argue that the spatial distribution of crime is affected by the environmental features that motivate or restrain criminal activities (Wortley & Townsley, 2016). Rational choice theory, social disorganization theory, strain theory and routine activities theory are frequently cited environmental criminology theories, which explain how crime patterns are determined by different physical or social characteristics, such as income inequality. Figure 4-1 summarizes the conceptual framework for modelling crime patterns in this study based on such criminology theories.

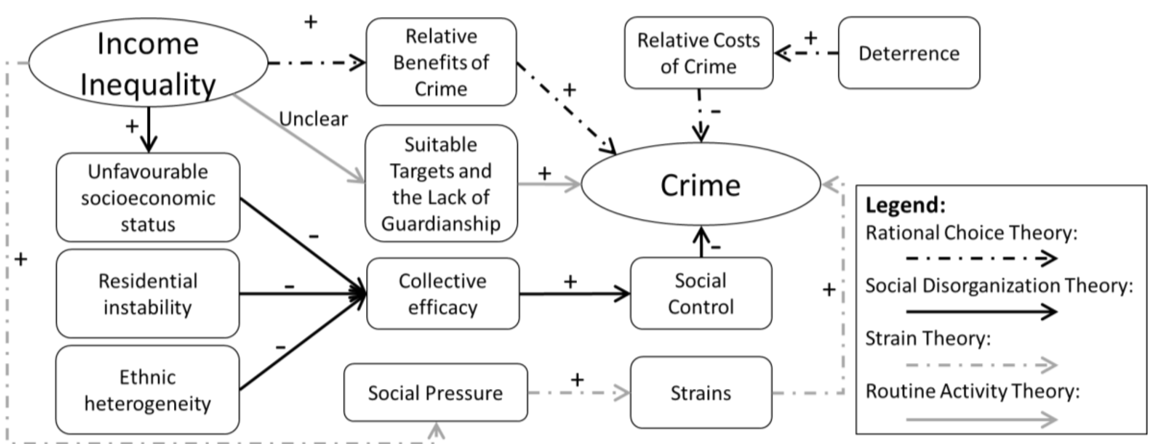


Figure 4-1. Conceptual framework for modelling crime patterns based on environmental criminology theories ("+" represents a positive association and "-" represents a negative association).

Rational choice theory, originated by Becker (1968), views criminal behaviours as normal economic activities. According to this theory, people voluntarily and knowingly choose to violate laws after making rational considerations of the costs and benefits of both legal and illegal activities (Cornish & Clarke, 1986). When there is significant income inequality, low-income individuals may believe that directly making benefits from high-income individuals via criminal offences may bring about higher returns than retaining normal market activities (Chiu & Madden, 1998; McCarthy, 2002). Moreover, deterrence plays an essential role in this theory. When criminals are not likely to be severely punished by either formal justice systems or informal social sanctions, the costs of offending reduce comparatively and hence people are more likely to opt for criminal activities (Anderson et al., 1977; Grasmick & Bursik, 1990).

Social disorganization theory, initially presented by Park and Burgess (1925) and formally developed by Shaw and McKay (1942), links crime to community environment characteristics. Research has associated adverse community characteristics, such as low socioeconomic status (low income, low education attainments, etc.), residential instability and ethnic heterogeneity, with high levels of violence and crime (Bursik & Grasmick, 1999; Elliot et al., 1996; Sampson & Groves, 1989). It is argued that the intervening variable between these community characteristics and crime rates is collective efficacy, which reflects social cohesion and the shared attitudes among community members towards social control (Sampson et al., 1997). In other words, the socioeconomic and demographic conditions in socially disorganized communities create barriers for residents to realize common values and hence weaken crime control. Income inequality, as part of unfavourable socioeconomic status, participates in the social disorganization process by increasing social distance and reducing interactions among community members (Hipp, 2007).

Strain theory highlights the impacts of social environments on individual mental status and negative emotions, such as frustration and anger. Individuals who are in a struggle to achieve socially valued goals (usually monetary success) tend to experience strains and frustrations, which can further lead to more negative thoughts and ultimately motivate them to commit criminal offences (Cohen, 1955; Merton, 1938). Agnew (1992) emphasizes the role of the social comparison process referenced in this theory. When the relatively poor population compare themselves to the more affluent population, they may perceive a sense of inequality and unfairness, which increases their strains and distress and may drive them to participate in risky and illegal actions and behaviours.

Differing from most criminology theories, routine activities theory focuses on crime opportunities in daily activities. This theory states that a crime incident requires the presence of a suitable target, a potential offender, and the lack of guardianship at the same location and time (Cohen & Felson, 1979). As a result, criminal offending tends to cluster in areas with abundant crime opportunities, such as business areas without video surveillance. Widening income inequality could change the crime opportunity structure in multiple directions. For example, when the income gap is large, more affluent people can become more attractive targets to the poor, but they might also be able to afford better security measures (i.e., guardianship) against potential offenders (Madero-Hernandez & Fisher, 2012).

4.2.2 Frequentist and Bayesian Approaches in Crime Research

Frequentist regression models have been widely applied in the analysis of risk factors for crime. The ordinary least squares (OLS) model, which finds optimal parameter estimates by minimizing the sum of squared differences between the predicted values and the observed values of the dependent variables, is a commonly used method in frequentist regression (Weisberg, 2005). However, the OLS model may be problematic in spatial data analysis due to the common issue of spatial autocorrelation. Spatial autocorrelation refers to the systematic variation in a variable across space, including positive spatial autocorrelation, where similar values tend to cluster, and negative spatial autocorrelation, where neighbouring values tend to be dissimilar (Haining, 1990). To verify the existence of spatial autocorrelation, multiple test statistics can be calculated, such as global Moran's I and global Geary's C (Cliff & Ord, 1973). When spatial autocorrelation exists, spatial regression models, instead of classical regression models which assume spatial randomness, should be used to prevent biased results while analyzing crime in cross-sectional geographic units (Anselin, 1988; Anselin et al., 2000). Various frequentist spatial regression models have been developed, such as the spatial lag model and the spatial error model (Anselin, 1988).

Although the use of frequentist regression is commonly accepted in crime research, some studies have instead suggested the use of Bayesian regression approaches. Frequentist inference and Bayesian inference are two statistical inferential paradigms to make estimates of parameters while modelling real-world processes. In contrast to frequentist statistics, which considers parameters as unknown constants, Bayesian statistics considers parameters as random variables and provides probability statements of the parameter values by combining prior knowledge and the observed data based on Bayes' theorem (Bolstad & Curran, 2016). Law et al. (2014) argue that Bayesian regression is a preferable approach in small-area crime analysis for several reasons: (1) Bayesian models in hierarchical structures can integrate crime information from different sources; (2) Bayesian methods are able to fit more complex spatial models due to the use of Markov Chain Monte Carlo (MCMC) simulation; (3) while frequentist spatial regression is designed for analyzing continuous crime rates, Bayesian regression can model discrete crime counts; (4) the Bayesian approach has a better handle of the small number problem, where low crime counts in small areas lead to unstable parameter estimates. Furthermore, the Bayesian approach provides a convenient way of modelling the interactions between multiple types of crime, which can potentially improve model performance (e.g., Liu & Zhu, 2017; Quick et al., 2018). Despite these advantages, Bayesian modelling does not necessarily produce more accurate results compared to frequentist modelling. Wakefield (2013) states that issues such as parameter interpretation and model misspecification are much more important than the inferential approach adopted and suggested that the frequentist and Bayesian approaches can be applied to the same data to compare the results and to attain a better understanding of spatial effects.

4.3 Study Area and Data Sources

This study uses data from the City of Toronto, the core of the largest metropolitan area in Canada. Toronto has a population of over 2.7 million according to the 2016 census and around half of them are immigrants to Canada (Statistics Canada, 2019). Characterized by highly diverse demographics, Toronto has experienced increasing inequality and polarization during the past few decades (Walks, 2014). Although Toronto is known as a safe city compared to most major metropolitans in the world, the crime severity index, which indicates both the amount and seriousness of police-reported crime, has increased for five consecutive years since 2014 (Statistics Canada, 2020b).

Previous studies about income inequality and crime have applied various spatial units and boundaries of analysis, since there is no universal standard when selecting spatial units. To investigate the effects of spatial scale, this study adopts two census geographic units, census tracts (CT) and dissemination areas (DA). Both CTs and DAs are relatively small and stable over time. Each CT usually has a population between 2,500 and 8,000 while a DA usually has a population between 400 and 700 (Statistics Canada, 2018a, 2018b). There are 572 CTs and 3,702 DAs in Toronto and all DAs are wholly nested within CTs. 5 CTs and 67 DAs within the study area did not have complete data or spatial neighbours (for the purpose of spatial modelling) and were therefore excluded from this study. Figure 4-2 illustrates the boundaries of CTs and DAs in the study area and the excluded areas are marked. The excluded areas only have 0.4% of the City's population, thus should not have significant impacts on the analysis results.

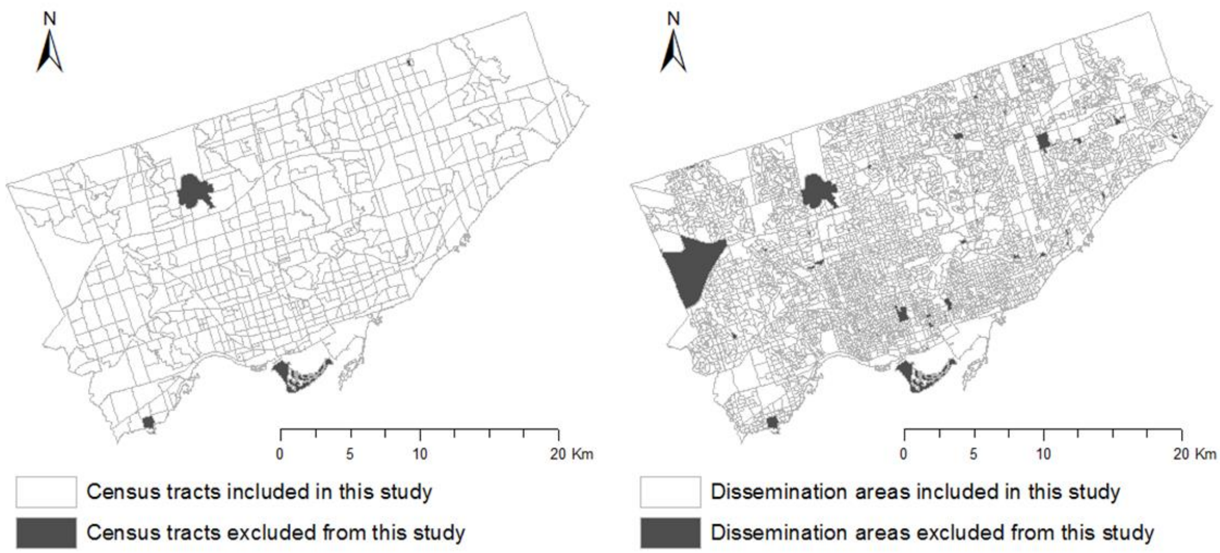


Figure 4-2. Census tracts (left) and dissemination areas (right) in the City of Toronto (areas excluded from this study are marked).

Data required for the calculation of income inequality and other regression variables in Toronto CTs and DAs were extracted from the 2016 census of Canada (Statistics Canada, 2020c). The census data provides statistics with different themes as well as the census boundaries at different census scales across Canada. Major crime occurrences were represented by the major crime indicators data retrieved from the Toronto Police Public Safety Data Portal in June 2020 (Toronto Police Service, 2020b). This data records the dates and locations of incidents of five major crime types (assault, robbery, auto theft, break and enter, and theft over $5,000) between 2014 and 2019. Crime counts and crime rates of each major crime type between 2015 and 2019 in Toronto CTs and DAs were quantified based on the crime data, census boundaries and census population.

4.4 Methodology

4.4.1 Exploratory Spatial Data Analysis of Crime

With a goal to examine the dependence of five major crime types on income inequality, the overall workflow of this study is illustrated in Figure 4-3. Before regression modelling, exploratory spatial data analysis (ESDA) was undertaken to examine and compare the spatial patterns of different types of crime. By definition, ESDA is a series of techniques to depict spatial distributions, identify clusters, outliers or different forms of spatial associations, and indicate spatial heterogeneity (Anselin, 1998). In this study, the purpose of ESDA was to explore the strength of spatial effects to decide on the necessity to apply spatial regression models and whether Bayesian modelling may be appropriate to account for the interactions between crime types.

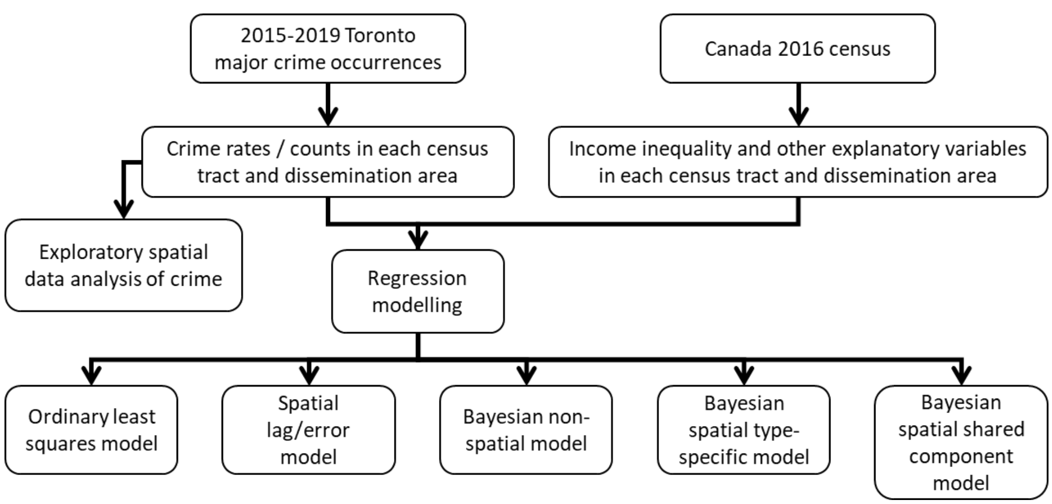


Figure 4-3. Methodology for modelling the impacts of income inequality on major crimes in the City of Toronto.

First, the commonly used global Moran's I was calculated for each crime type to identify the presence of global spatial autocorrelation. Second, local spatial patterns of crimes were identified using local indicators of spatial associations (LISA), which is a fundamental ESDA toolset that indicates the level of significant spatial clustering of similar values around each observation in a dataset (Anselin, 1995). For a variable, LISA can be computed in every observed location to decide the local spatial cluster type, and commonly used LISA statistics include local Moran's I, local Geary's C and Getis-Ord G/G*(Anselin, 1995; Getis & Ord, 1992). In this study, local Moran's I was employed to visualize the distribution of spatial clusters (hot spots, cold spots, and local outliers) for each crime type across the study area. The pseudo significance levels of global and local statistics were determined using permutation tests, which compare the actual values with simulated values obtained from spatial randomization processes (Anselin, 1995).

4.4.2 Income Inequality Variables and Control Variables

As a small-area analysis, this study considers both within-area and across-area income inequality. Within-area income inequality is usually measured by income inequality indices. In the literature, there have been a variety of income inequality indices and the Gini coefficient is the most commonly used metric (Allison, 1978; De Maio, 2007). The Gini coefficient measures the deviation of the observed income distribution from an equal income distribution, and it reflects relative deprivation, which refers to the lack of resources for the poorer population to maintain a quality of life comparable to the relatively affluent population (Townsend, 1979; Yitzhaki, 1979). In this study, the Gini coefficient was calculated with the after-tax household income data from the census, which is recorded as the numbers of households in 18 income categories in each CT or DA, including an open-ended category at the top range (> $150,000). To calculate the income distribution in each area, the midpoint of each income category was used to represent every household that falls in the category. Income for the top open-ended category was inferred based on the average income obtained from the census data and the estimated cumulated income in the first 17 categories. The Gini coefficient ranges from 0% to 100% and a greater value indicates a higher level of income inequality. Note that without income data for each individual household available, the income distribution calculated for each area is only an aggregate approximation and the derived Gini coefficient values are inevitably inaccurate. Figure 4-4 depicts the Gini values in Toronto CTs and DAs.

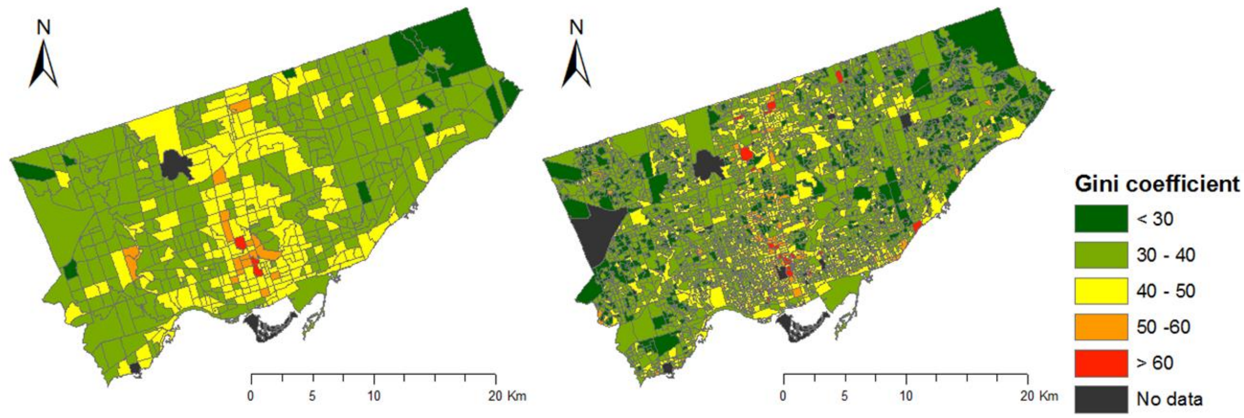


Figure 4-4. Maps of the Gini coefficient at the CT (left) and DA (right) scales.

Based on routine activities theory, potential offenders identify favourable crime environments and encounter suitable targets in their daily routines (Brantingham & Brantingham, 1993; Cohen & Felson, 1979). At the small area level, residents' daily routines may not be restricted within their areas of residence, since they are mobile and may travel for work, recreation, etc. As a result, offenders can be motivated by the economic disparities between neighbouring areas and commit crimes outside their area of residence, which makes it important to account for across-area income inequality (Metz & Burdina, 2018; Wang & Arnold, 2008). Since the Gini coefficient only reflects within-area income inequality, based on Metz and Burdina (2018), an indicator of income gaps between neighbouring areas is derived as:

$$\%\text{ richer than the poorest neighbour} = \frac{Inc - MinNeiInc}{MinNeiInc} \times 100\%, \quad (4\text{-}1)$$

where Inc is the median after-tax household income in an area and $MinNeiInc$ is the minimum median after-tax household income in its neighbouring areas. In this study, neighbours were defined as different areas that share at least one vertex or edge (i.e., defined as queen contiguity). Figure 4-5 depicts the values of % richer than the poorest neighbour in CTs and DAs.

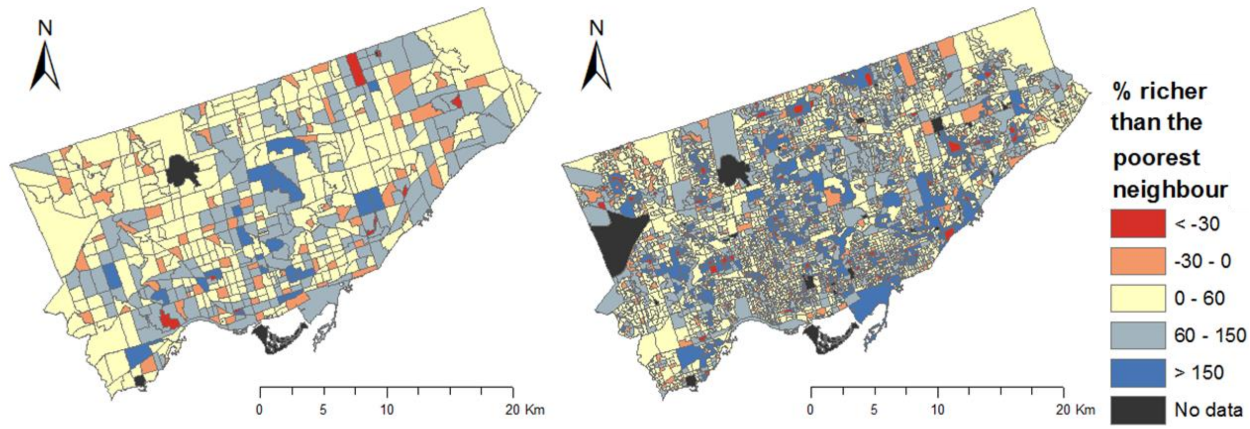


Figure 4-5. Maps of % richer than the poorest neighbour at the CT (left) and DA (right) scales.

In addition to the two income inequality variables, several control variables were included as explanatory variables in the regression models. When the number of explanatory variables increases, one important issue that could reduce the reliability of the regression results is multicollinearity, which refers to the linear correlations between multiple explanatory variables (Alin, 2010). In this study, the condition number was employed to diagnose multicollinearity and the threshold of 30 was used to define strong multicollinearity (Belsley, 1991). Different combinations of control variables were tested to adjust for strong multicollinearity and four variables corresponding to the major risk factors indicated by criminology theories were finally selected. To quantify the impacts of residential instability, ethnic heterogeneity and low education attainments, % movers (percent of the residents that moved within the past five years), ethnic fractionalization and % no post-secondary degrees (percent of the residents aged 25+ without post-secondary degrees) were included. Ethnic fractionalization is calculated by the following function:

$$\text{Ethnic fractionalization} = (1 - \sum \pi_i^2) \times 100\% \tag{4-2}$$

where π_i is the proportion of residents that identify themselves in ethnic group i.

As indicated by social disorganization theory, these three control variables are expected to be positively associated with crime rates. Poverty or low income, as an important part of low socioeconomic status, has also been frequently considered in previous research. However, an additional poverty variable would lead to strong multicollinearity at the CT scale, and in the testing process, the inclusion of a poverty variable had little impact on the key results (i.e., the impacts of the income inequality variables). Thus, it was decided not to include poverty in the regression. The fourth control variable in regression modelling was population density (thousand residents per square kilometre), which was found to be negatively associated with crime rates and linked to the depopulation of unsafe areas (i.e., residents moving out of areas with high crime rates) and the deterrence effects in populated areas in previous studies (Metz & Burdina, 2018; Morenoff et al., 2001; Patino et al., 2014). Descriptive statistics for the explanatory variables are provided in Appendix A.

4.4.3 Frequentist Models

The OLS model was used as a benchmark frequentist method. For crime type k, the natural log of the crime rate in area i ($\log(Y_{ki})$) is given by the following function:

$$\log(Y_{ki}) = \alpha_k + X_i\beta_k + e_{ki}, \tag{4-3}$$

where α_k is an intercept term; X_i is a column vector of explanatory variables in area i; β_k is a row vector of regression coefficients for crime type k; and e_{ki} is a random error term.

The OLS model assumes spatial independence in the dependent variable. Therefore, if spatial autocorrelation exists, the OLS results are expected to be biased and inaccurate. In addition to the ESDA of crime, this study used Lagrange Multiplier (LM) test statistics, which detect model misspecification caused by spatial autocorrelation and aid in deciding which spatial regression model to use (Anselin, 1988). For each crime type, the LM-lag statistic and LM-error statistic were computed, which were all found to be significant. Following the methodology described by Anselin (2005), robust LM statistics were further compared. If the robust LM-lag statistic was more significant, the spatial lag model was adopted; if the robust LM-error statistic was more significant, the spatial error model was adopted. The spatial lag model and spatial error model include an additional term each based on the notion of a spatial lag (the spatial lag of a value is the average value of its spatial neighbours). These are given by Equation 4-4 and Equation 4-5, respectively:

$$\log(Y_{ki}) = \rho_k Wy_{ki} + \alpha_k + X_i\beta_k + e_{ki}, \tag{4-4}$$

where Wy_{ki} is the spatial lag for the dependent variable of crime type k in area i; ρ_k is the spatial autoregressive coefficient for crime type k.

$$\log(Y_{ki}) = \alpha_k + X_i\beta_k + We_{ki}\lambda_k + e_{ki}, \tag{4-5}$$

where We_{ki} is the spatial lag for the error of the crime type k in area i and λ_k is the spatial autoregressive multiplier for crime type k.

Note that in frequentist modelling, the crime rate is defined as one plus the crime count in a five-year period (2015-2019), divided by the population (one was added to every crime count to avoid zeros in the log transformation). In the literature, both single-year and multiple-year measures of crime have been widely used and it is difficult to compare their appropriateness (He et al, 2015). In this study, considering that crime rates in small areas tend to experience high volatility, the multiple-year measure is deemed to better represent the risk of crime. Descriptive statistics for the log-transformed crime rates are provided in Appendix A.

4.4.4 Bayesian Models

Hierarchical regression models were employed to examine the relationship between income inequality and crime in the Bayesian framework. Unlike the frequentist regression approach, where crime rates are directly calculated with the crime counts and census population in each area, crime counts are modelled as Poisson distributed random variables in Bayesian regression:

$$O_{ki} \sim Poisson(p_i\mu_{ki}), \tag{4-6}$$

where O_{ki} is the five-year crime count of crime type k in area i; p_i is the population in area i; and μ_{ki} is the five-year crime rate of crime type k in area i.

Similar to frequentist regression, a non-spatial model, given by Equation 4-7, was used as a benchmark Bayesian method. In a similar form to the OLS model, this model assumes spatial independence. For crime type k, the natural log of crime rate ($\log(\mu_{ki})$) is expressed as the sum of an intercept term (α_k), the product of the explanatory variable vector and the regression coefficient vector ($X_i\beta_k$), and a spatial random error term (e_{ki}). All explanatory variables are centred at their means. The centred variables improve the efficiency of MCMC sampling and have no impact on the estimates of the regression coefficients (Lawson, 2018).

$$\log(\mu_{ki}) = \alpha_k + X_i\beta_k + e_{ki}, \tag{4-7}$$

In Bayesian modelling, priors are required for unknown parameters. In this model, vague priors were used since there is little prior knowledge. For each crime type, α_k is given a uniform distribution; every regression coefficient in β_k is given a normal distribution with the mean equal to 0 and the variance equal to 1000; e_{ki} is given a normal distribution with the mean equal to 0 and the variance equal to σ_{ek}^2 . σ_{ek}^2 is modelled in a commonly used distribution of $Gamma(0.5,0.0005)$.

To account for the spatial autocorrelation in crime, the second Bayesian model is a type-specific model that quantifies the structured spatial effects in each crime type separately. This model is based on the well-known BYM structure proposed by Besag et al. (1991). As shown in Equation 4-8, this model includes a structured spatial error term (s_{ki}), which has an intrinsic conditional autoregressive (ICAR) prior. The ICAR model assumes positive spatial autocorrelation and s_{ki} is normally distributed with the mean equal to the spatial lag of s_{ki} and the variance equal to σ_{sk}^2/n_i, where n_i is the number of neighbouring areas to area i. σ_{sk}^2 was given the same Gamma distribution as σ_{ek}^2.

$$\log(\mu_{ki}) = \alpha_k + X_i\beta_k + (s_{ki} + e_{ki}), \tag{4-8}$$

Considering the interactions between different crime types, a spatial shared component model is employed as the final model in this study. These interactions are supported by criminology theories (e.g., the broken window theory, introduced by Wilson & Kelling., 1982, indicating that high crime rates of less serious crimes can lead to the presence of more serious crimes), visual inspection of the crime maps (see Section 4.5.1), and the bivariate correlations between crime types (provided in Appendix A). As shown in Equation 4-9,

$$\log(\mu_{ki}) = \alpha_k + X_i\beta_k + (s_{ki} + e_{ki}) + l_k\phi_i, \tag{4-9}$$

this model includes an additional shared spatial component ($l_k\phi_i$), where ϕ_i is the spatial effect in area i shared by all crime types and l_k is the factor loading of crime type k for ϕ_i. This model assumes that all crime types are positively associated, but every crime type has a unique association with the shared spatial effects. For each crime type, l_k is given a positive half-normal prior distribution with the mean equal to 0 and the variance equal to 1000. ϕ_i is given an ICAR distribution with the variance fixed to 1. Since this model involves factor analysis, without constraints, there can be multiple equivalent solutions that prevent the MCMC chains from convergence. The fixed variance and the positive factor loadings act as an identifiability constraint in the priors and guarantee a unique solution to l_k and ϕ_i (Tzala & Best, 2008).

4.5 Results

4.5.1 Spatial Patterns of Crime

The ESDA of crime was performed in GeoDa, a software package designed for spatial data analysis (Anselin et al., 2010). Table 4-1 shows the global Moran's I statistics for log-transformed crime rates in Toronto CTs and DAs. Pseudo p-values were computed through 9,999 permutations to determine the significance of spatial autocorrelation. The statistics indicate strongly positive global spatial autocorrelation in every log-transformed crime rate. Local Moran cluster maps for log-transformed crime rates are shown in Figure 4-6 and Figure 4-7. 9,999 permutations were applied and the p-value of 0.05 was used to examine the presence of significant spatial patterns in each area. These maps clearly show crime hot spots and cold spots for each crime type, which further provides evidence of the presence of positive spatial autocorrelation. At both scales, large hot spots are found around the downtown areas in the south for all crime types except auto theft. Although auto theft has a different pattern in the downtown areas, it still shares some similarities with other crime types, such as the hot spots in the northwestern section and the cold spots in the middle section of the city. These ESDA results provide evidence that supports the use of spatial models and the Bayesian shared component model in regression analysis. Note that these statistics are all based on the natural logs of crime rates, which were used as dependent variables in the regression models. ESDA was also applied to raw crime rates and the spatial patterns were found to be similar to these results.

Table 4-1. Global Moran's I statistics for log-transformed crime rates

Crime type	Assault	Robbery	Auto theft	Break and enter	Theft over $5,000
Census tracts					
Global Moran's I	0.229	0.194	0.251	0.238	0.148
Pseudo p-value	0.0001	0.0001	0.0001	0.0001	0.0001
Dissemination areas					
Global Moran's I	0.169	0.147	0.206	0.155	0.115
Pseudo p-value	0.0001	0.0001	0.0001	0.0001	0.0001

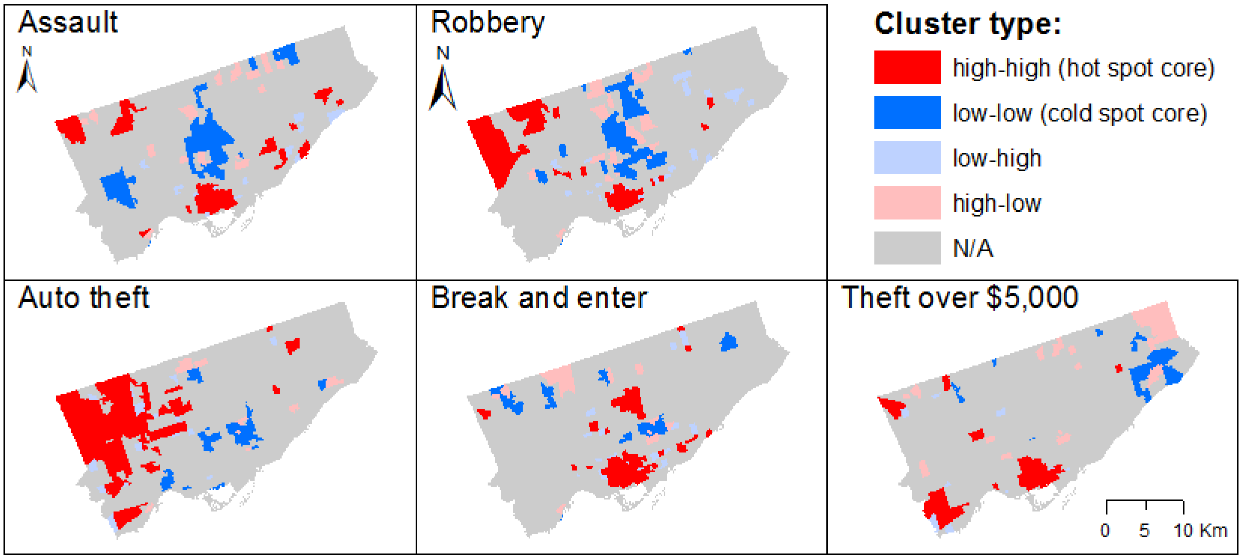


Figure 4-6. Local Moran's I clusters of log-transformed crime rates at the CT scale ($p < 0.05$).

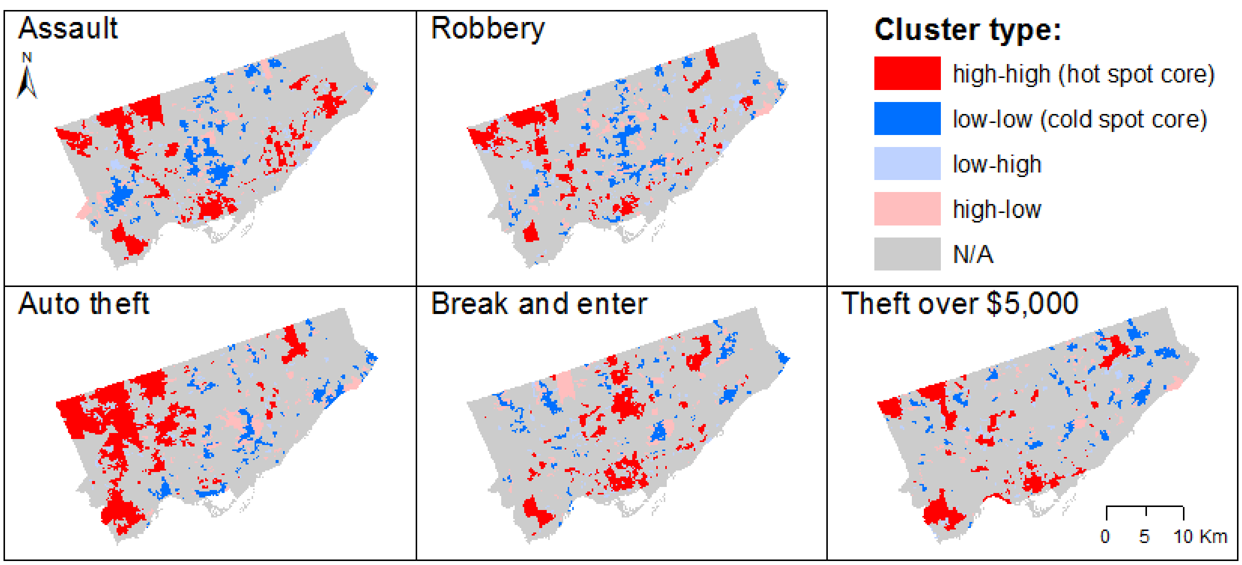


Figure 4-7. Local Moran's I clusters of log-transformed crime rates at the DA scale ($p < 0.05$).

4.5.2 Frequentist Regression Results

Frequentist regression was implemented in GeoDa, where regression reports with significance test results and diagnostic statistics were generated (Anselin et al., 2010). Since this manuscript only addresses the impacts of income inequality, Table 4-2 shows the regression coefficient estimates of the two income inequality variables obtained from the frequentist models. Complete frequentist regression results with regression coefficient estimates of the four control variables are provided in Appendix B. The commonly used cut-off p-value of 0.05 was used to determine significant associations. At the CT scale, the impacts of the Gini coefficient are significantly positive on all crime types except auto theft in the OLS results, but its impact on robbery is not significant in the spatial model results. The impacts of % richer than the poorest neighbour are significantly positive on all crime types except robbery in the OLS results and at the CT scale, but only its positive associations with break and enter and theft over $5,000 are significant in the CT-level spatial model results. At the DA scale, the impacts of the Gini coefficient are significantly positive on all crime types in the spatial model results, but its association with auto theft is not significant in the OLS results. The impacts of % richer than the poorest neighbour at the DA level are significantly positive on all crime types in both the OLS and spatial model results.

Table 4-2. Frequentist regression results for the income inequality variables

Census tracts:		**Assault**	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Gini Coefficient	**OLS**	0.029*	0.019*	0.009	0.043*	0.023*
	Spatial	0.022*	0.012	0.004	0.033*	0.019*
% richer than the poorest neighbour	**OLS**	0.002*	0.001	0.002*	0.004*	0.003*
	Spatial	0.001	0.000	0.001	0.003*	0.002*
Dissemination areas:		**Assault**	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Gini Coefficient	**OLS**	0.022*	0.018*	0.004	0.025*	0.013*
	Spatial	0.019*	0.015*	0.005*	0.021*	0.011*
% richer than the poorest neighbour	**OLS**	0.002*	0.001*	0.001*	0.002*	0.001*
	Spatial	0.001*	0.001*	0.001*	0.002*	0.001*

Note: Each regression analysis includes six explanatory variables. This table only shows the results for the income inequality variables. Either the spatial lag model or the spatial error model was used as the spatial model (See Appendix B for detail). * indicates $p < 0.05$.

4.5.3 Bayesian Regression Results

Bayesian regression analysis was implemented in WinBUGS, a statistical software tool that uses the MCMC method to generate posterior distributions for model parameters (Spiegelhalter et al., 2003). WinBUGS code for the shared component model (Equation 4-9) is provided in Appendix C. For each model at each spatial scale, two parallel MCMC chains with different initial values were run. Convergence was reached by 50,000 iterations for each model and posterior statistics were obtained from additional 50,000 iterations after convergence. The Monte Carlo error for each parameter is smaller than 5% of its posterior standard deviation, indicating that the number of iterations to generate the posterior distribution was sufficient (Spiegelhalter et al., 2003). Table 4-3 shows the Bayesian regression results for the income inequality variables. Each regression coefficient is represented by its posterior mean and 95% credible interval (recorded within parentheses). Regression coefficients that are consistently positive or negative at the 95% credible interval are considered significant. Bayesian regression results for the four control variables can be found in Appendix D.

The Bayesian non-spatial results indicate the same associations as the OLS results in terms of significance, but the Bayesian spatial results are different from the frequentist spatial results. At the CT scale, in both the type-specific model and the shared component model, the Gini coefficient is only positively associated with break and enter, while % richer than the poorest neighbour has no positive effects. In the shared component model only, the negative effects of % richer than the poorest neighbour on assault and robbery are significant at the CT scale. The results at the DA scale are more consistent between Bayesian non-spatial and spatial models. In the type-specific model results, the Gini coefficient is positively associated with all crime types except auto theft, which is consistent with the non-spatial results, but its association with assault was insignificant in the shared component model. For % richer than the poorest neighbour, its impacts on all crime types at the DA level are significantly positive in all Bayesian models.

Table 4-3. Bayesian regression results for the income inequality variables

Census tracts:		Assault	Robbery	Auto theft	Break and enter	Theft over $5,000
Gini Coefficient	**Non-spatial model**	0.029* (0.014, 0.044)	0.022* (0.005, 0.038)	0.007 (-0.006, 0.020)	0.043* (0.031, 0.055)	0.027* (0.011, 0.042)
	Type-specific model	0.005 (-0.011, 0.021)	0.001 (-0.018, 0.019)	-0.002 (-0.016, 0.011)	0.021* (0.008, 0.034)	0.011 (-0.007, 0.028)
	Shared component model	-0.003 (-0.017, 0.010)	-0.007 (-0.023, 0.008)	-0.009 (-0.021, 0.003)	0.015* (0.004, 0.026)	0.000 (-0.015, 0.015)
% richer than the poorest neighbour	**Non-spatial model**	0.002* (0.000, 0.004)	0.001 (-0.001, 0.003)	0.002* (0.000, 0.003)	0.004* (0.002, 0.005)	0.003* (0.001, 0.005)
	Type-specific model	-0.001 (-0.003, 0.001)	-0.002 (-0.004, 0.000)	0.001 (-0.000, 0.002)	0.001 (-0.000, 0.003)	0.002 (-0.000, 0.003)
	Shared component model	-0.002* (-0.003, -0.001)	-0.003* (-0.004, -0.001)	0.000 (-0.001, 0.001)	0.001 (-0.001, 0.002)	0.000 (-0.001, 0.002)
Dissemination areas:		**Assault**	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Gini Coefficient	**Non-spatial model**	0.026* (0.019, 0.032)	0.029* (0.021, 0.038)	0.003 (-0.003, 0.009)	0.029* (0.024, 0.035)	0.030* (0.022, 0.038)
	Type-specific model	0.013* (0.006, 0.019)	0.019* (0.010, 0.028)	0.002 (-0.003, 0.008)	0.014* (0.008, 0.019)	0.015* (0.006, 0.024)
	Shared component model	0.007 (-0.000, 0.014)	0.013* (0.004, 0.022)	0.000 (-0.007, 0.006)	0.010* (0.004, 0.016)	0.010* (0.001, 0.019)
% richer than the poorest neighbour	**Non-spatial model**	0.002* (0.001, 0.002)	0.002* (0.001, 0.003)	0.001* (0.001, 0.002)	0.002* (0.002, 0.002)	0.002* (0.001, 0.003)
	Type-specific model	0.001* (0.001, 0.002)	0.001* (0.001, 0.002)	0.001* (0.001, 0.002)	0.001* (0.001, 0.002)	0.002* (0.001, 0.002)
	Shared component model	0.001* (0.000, 0.002)	0.001* (0.000, 0.002)	0.001* (0.001, 0.002)	0.001* (0.001, 0.002)	0.001* (0.001, 0.002)

Note: Each regression analysis includes six explanatory variables. This table only shows the results for the income inequality variables. * indicates consistent sign at the 95% credible interval.

4.6 Discussion

4.6.1 Comparing Regression Results of Different Models

This research considered five crime types, two income inequality variables, and two spatial scales, resulting in 20 possible links assessed between income inequality and crime in this study. Focusing on the significant relationships only, some discrepancies are observed in the results of different statistical models. In the frequentist approach, the OLS results indicate 17 significantly positive associations, but three of them are insignificant in the spatial model results. Moreover, one significantly positive association indicated by the spatial model results is insignificant in the OLS results. Since the ESDA results and the LM-statistics indicate the presence of significant spatial autocorrelation, the OLS model might produce biased results in which some associations could be either underestimated or overestimated (Anselin et al., 1996; Ward & Gleditsch, 2008).

In order to further assess the model fit, the Akaike information criterion (AIC) was computed for each frequentist model. The AIC, formulated by Akaike (1973), indicates the model performance by handling the trade-off between the goodness-of-fit and model complexity. Models with smaller AICs, by four or more, are considerably better and models with larger AICs, by ten or more, can be excluded from further analysis (Burnham & Anderson, 1998). Table 4-4 shows the AIC results, where the spatial models have significantly lower AICs than the OLS models in all cases. This implies that the spatial models have an improved goodness of fit compared to the non-spatial approach, suggesting that the spatial model results may be more reliable in assessing the income inequality-crime relationships.

Table 4-4. Akaike information criterion values of the frequentist regression models

Census tracts:	**Assault**	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
OLS	1515	1543	1294	1266	1339
Spatial model	1478	1508	1230	1222	1331
Dissemination areas:	**Assault**	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
OLS	11463	10253	9280	9794	7679
Spatial model	11412	10187	9100	9698	7644

As for the income inequality variables in the Bayesian results, the non-spatial model indicates 17 significantly positive associations, but seven of them are insignificant in the type-specific model results. Among the 10 significantly positive associations suggested by the type-specific model results, one is insignificant in the shared component model results. Moreover, the shared component model indicates two significantly negative associations between % richer than the poorest neighbour and crime, which are not evident in the other models. The Deviance Information Criterion (DIC) was used to evaluate the Bayesian models. The DIC is a generalized form of the AIC in Bayesian hierarchical modelling and the rules of comparing AICs also work for the DICs, as long as the differences between DICs are not caused by Monte Carlo errors (Spiegelhalter et al., 2002).

Table 4-5 shows the DIC results, where the non-spatial models have the highest DIC values and the shared component models have the lowest DIC values. Note that all crime types had to be included in one model in the shared component model, which produced a single DIC value at each spatial scale. In order to compare DIC values between models, for the non-spatial model and the type-specific model, the five types of crime were also included in one model instead of five separate models. Nevertheless, these two models were also tested for each crime type separately. The regression results remain the same and for every crime type, the type-specific model resulted in a smaller DIC than the non-spatial model. These DIC values indicate that the type-specific model tends to outperform the non-spatial model, while the shared component model further improves the model fit. Since the spatial autocorrelation of each crime type and the interactions between crime types are evident (See Section 4.5.1), it is reasonable to find the shared component model to have the best model fit.

Table 4-5. Deviance information criterion values of the Bayesian regression models

	Census tracts:	**Dissemination areas:**
Non-spatial model	19938	80410
Type-specific model	19901	80068
Shared component model	19560	77215

Inconsistencies can also be found between the frequentist and Bayesian results. When considering the best-fitting frequentist model (frequentist spatial models) and Bayesian model (the shared component model), discrepancies in regression coefficient estimates could be caused by the differences in the model specifications as well as the different inferential approaches. First, crime rates were directly calculated using crime counts and populations in the frequentist models while the Bayesian method modelled crime using Poisson distributions. Second, the frequentist spatial models include a spatially lagged term (lagged dependent variables or lagged errors) to adjust for spatial autocorrelation while the Bayesian spatial models take advantage of the MCMC algorithm and use the ICAR model to represent the structured spatial errors. Moreover, the shared component model includes a spatial shared component to model the interactions between crime types, which could not be applied to the frequentist models.

Given that Bayesian modelling can properly account for the count data, the small number problem, and the interactions between multiple dependent variables, Bayesian regression models may be preferable compared to frequentist regression for the purposes of this study. However, this does not necessarily mean that the associations found to be significant only in the frequentist spatial results are invalid. Since the frequentist spatial model results and the Bayesian shared component model results are not conflicting, that is, no association is found significantly positive in one model but significantly negative in the other model, both results are retained and considered in the discussion of the income inequality-crime relationships.

4.6.2 The Income Inequality-Crime Relationship and the Issue of Spatial Scale

Based on the best-fitting frequentist and Bayesian models, different impacts of within-area income inequality (i.e., the Gini coefficient) and across-area income inequality (i.e., % richer than the poorest neighbour) on five major crime types have been identified at the CT and DA scales. At the CT scale, there is a strongly positive association between within-area income inequality and break and enter, since the significance of this association is not sensitive to the choice of regression model. Within-area income inequality may also have positive relationships with assault and theft over $5,000, as indicated by the frequentist spatial model results. These positive effects are in agreement with the expectation that within-area income inequality may be a driver of higher crime rates.

For across-area income inequality, the frequentist results highlight the positive impacts of % richer than the poorest neighbour on two property crime types, namely break and enter and theft over $5,000 at the CT scale. This matches the findings of Metz and Burdina (2018), who applied similar income inequality measures and indicated that larger income disparities between neighbouring areas may motivate residents from poorer areas to steal from richer areas. On the other hand, the Bayesian results indicate negative impacts of the across-area income inequality measure on two violent crime types (assault and robbery) at the CT level, which means that violent crimes are more likely to occur in poorer CTs than in their richer neighbours. This could be explained by social disorganization theory. As described in Section 4.2.1, this theory indicates that poor socioeconomic conditions create difficulties for community members to realize common values and implement effective social control. Among neighbouring CTs, poorer CTs may have worse social cohesion and social control within communities and hence provide more suitable environments for breeding violent behaviour compared to more affluent DAs.

At the DA scale, positive impacts of within-area income inequality on robbery, break and enter, and theft over $5,000 are identified in both models and it may also have positive effects on assault and auto theft as indicated by the frequentist spatial model results. The effect of % richer than the poorest neighbour is significantly positive on all crime types in both models at the DA scale. The differences between the CT-level and DA-level results are a manifestation of the MAUP effects. When incidents are aggregated into larger spatial units, the crime levels in an area may disproportionately reflect some localized extreme patterns or mask some outlying local patterns (Weisburd et al., 2009). The ESDA results (Figure 4-6 and Figure 4-7 in Section 4.5.1) also illustrate the discrepancies between spatial scales in the crime patterns, especially since the DA scale seems to capture more detailed local variation.

The issue of scale is also important when considering the explanatory variables in the regression models. For example, for the two income inequality variables, some discrepancies between scales are not only explained by the generalization effects of the larger spatial unit. For within-area income inequality, when DA-level income data is aggregated into a CT, the across-

DA income disparities become part of within-CT income inequality. In an extreme case, a CT with a high Gini value could conceivably consist of several DAs with low Gini values but with very different income levels. For across-area income inequality, the spatial scale and size of spatial units also affect the distance between neighbouring areas. This could explain why the effects of % richer than the poorest neighbour are consistently positive at the DA scale. Since neighbouring DAs are within relatively short distances compared to neighbouring CTs, residents are usually knowledgeable about and able to travel to their nearby DAs. Thus, DAs that are richer than their neighbours may project a sense of inequality to residents in neighbouring DAs and subsequently attract potential criminals of all crime types, who try to “level the field” via illegal means.

4.6.3 Limitations and Future Research

This study has several limitations from both data and methodological perspectives. First, the quantification methods of deriving crime counts and crime rates are not ideal. According to Moreau (2019), the crime reporting rate in Canada was only 31% in 2014. This means that crime counts based on police-reported crime data might have ignored a significant number of unreported crime incidents. Census population counts were used as the denominator for calculating crime rates, similar to many other studies. However, it is recognized that the census population does not account for daytime population movements and hence it cannot accurately represent the at-risk population.

Second, the reliability of the demographic and socioeconomic variables was constrained by the census data and how it is counted and collected. Since census surveys are administered every five years, this study used variables from the 2016 census, which may not have been constant during the entire study period (2015-2019). Moreover, the Gini coefficients calculated in this study are also restricted by census income data and hence, were only approximated values.

Third, although this study quantified both the within-area and across-area income inequality, the two adopted measures do not encompass all dimensions of income inequality. The Gini coefficient cannot distinguish between different types of within-area income inequalities (e.g., income inequality among the lower-income or higher-income population) and hence, very similar values can represent different income distribution patterns (Cowell, 2011; De Maio, 2007). The across-area income inequality measure is also not ideal, since it only reflects the income disparity between each area and its poorest neighbour. There are evidently not many across-area income inequality measures available in the literature. Wang and Arnold (2008) present the localized income inequality index, which compares the income in each area with its spatial lag. This measure utilizes all neighbouring values, yet it could still nevertheless mask extreme values and potentially overlook some across-area income inequality patterns.

A fourth limitation regarding the across-area income inequality measures adopted in this study is the definition of the neighbouring areas and their boundaries themselves. This study used the commonly accepted first-order contiguity to define neighbouring areas, to quantify across-area income inequality, and to define spatial dependence for spatial regression analysis. However, residents in an area, especially at the DA scale, may be able to perceive across-area income inequality and commit crimes in areas farther away and beyond their first-order neighbours, since their routine activities may extend beyond adjacent areas. For spatial regression, how the definition of spatial structures can potentially impact the regression estimates remains debatable within the literature (e.g., Corrado & Fingleton, 2012; LeSage & Pace, 2014).

Future research could calculate crime rates and income inequality using different methods. For example, Andresen (2011) demonstrates the use of ambient population (24-hour average population) to calculate crime rates. Although using such alternative population data has its limitations (e.g., the boundaries and resolutions do not match other variables in the regression analysis), it is worth assessing how the income inequality-crime relationship is sensitive to the quantification of crime rates. Also, different at-risk populations can be adopted for different crime types (e.g., using the number of dwellings for break and enter). For within-area income inequality, other indices (e.g., Theil's measure) could be tested, while for across-area income inequality, future research could examine other definitions of neighbouring areas or develop new measures.

In terms of the regression models themselves, future research could conduct sensitivity tests using different spatial models and different spatial weights. It would also be useful to take advantage of the flexibility of Bayesian modelling to include other components. For example, Quick et al. (2018) demonstrate that including multiple shared spatial components that capture the interactions between different combinations of crime types can further improve the model fit.

Moreover, other control variables (e.g., a police activity variable to account for the deterrence effects) could be considered if the data is available. In addition, the investigation of the MAUP effects could be further extended. Future research could analyze other administrative spatial units or non-administrative spatial units based on other data sources.

4.7 Conclusions

By applying different regression models in the frequentist and Bayesian frameworks to five major crime types at the CT and DA scales in the City of Toronto, this study has found that the income inequality-crime relationship is sensitive to statistical models, crime types, and spatial units of analysis. This study has demonstrated that the use of spatial models can improve model fit and lead to some changes in the parameter estimates in both inferential frameworks and the Bayesian shared component model, which accounts for the interactions between crime types, can further enhance the overall model performance. Bayesian models have various advantages compared to frequentist models, especially in small-area studies such as in this study, where the frequentist models may be sensitive to even small variations in the data due to the small number problem. Nevertheless, results obtained from the best-fitting frequentist and Bayesian models in this study were not contradictory and were relatively consistent in their underlying conclusions.

The results of this study have implications for crime control and prevention in Toronto. First, although the degree of impact may vary for different crime types and different spatial scales, in general, results support within-area income inequality as being positively associated with crime. This is consistent with criminology theories, which suggest that higher levels of within-area income inequality may increase the relative benefits of crime, worsen social control, and create more attractive targets. Therefore, from a policy and planning perspective, more resources can be allocated to CTs and DAs with higher Gini values to improve crime prevention and control measures. Second, among neighbouring CTs, two major property crimes (break and enter and theft over $5,000) are more likely to occur in relatively affluent CTs, while two major violent crimes (assault and robbery) are more likely to occur in relatively poor or deprived CTs. Thus, relatively affluent CTs adjacent to poorer CTs may require more property protection measures, while relatively poor CTs adjacent to richer CTs may require more violence control measures. Third, all major crime types are more likely to occur in more affluent DAs compared to their poorer neighbours, which means that relatively rich DAs adjacent to more deprived DAs would require more attention and consideration in future crime control and prevention strategies, such as patrolling, deterrence, surveillance, and mitigation measures. These conclusions may also have consequences for other resource allocations, such as related healthcare and other social services.

Finally, this research reconfirms the notion commonly known in the social sciences that relative measurements of economic, political, or social deprivation are inextricably linked to social exclusion and feelings of stress that may drive criminal or deviant behaviours. As the relationship between income inequality and crime is evident in this research, a fundamental solution to crime control as well as all other income inequality-related social problems is to target and improve relative deprivation and individual wellbeing. Such measures have traditionally focused on policies that redistribute resources, such as transfer payments, universal basic education, and universal basic health services, which are thought to lessen relative deprivation. By addressing such underlying causes of income inequality and social exclusion, this enables individuals to feel less deprived and more included in society. As a result of such measures, fewer individuals may choose to participate in criminal activities and such individuals may instead opt to implement and practice social control.

Chapter 5: From the Spatial Variability to the Spatiotemporal Variability of Crime

The second manuscript (Chapter 4) investigates the relationship between income inequality and crime at the census tract and dissemination area scales in the City of Toronto. The results confirm the connections between the spatial variability of income inequality and the spatial variability of crime. Nevertheless, like many other crime studies, this manuscript focuses on the spatial patterns of crime and overlooks its temporal dimension. Crime incidents are not only concentrated around certain locations but also tend to occur at certain times of the year, week, and day. For example, crime incidents around beaches may occur most frequently during the summer, while crime incidents on bar streets may mostly occur on weekend nights. When such significant temporal variability of crime exists, aggregated crime data that average out the crime statistics over a long continuous time period (e.g., a year) may not reveal the true crime risks, and spatial analysis based on this data may produce misleading results.

Recognizing the importance of the temporal dimension of crime, the third manuscript (Chapter 6) presents a small-area spatiotemporal analysis at the dissemination area scale in Old Toronto, a district in the core of the City of Toronto. The Bayesian models used in the second manuscript are extended to include temporal components. The specific research problem to address is comparing the spatial patterns of crime between business days and non-business days. Different human activity patterns may occur on different days, which may result in different opportunities for offenders and risk factors for victims and then lead to the manifestation of significantly different spatial patterns of crime distributed throughout the city.

Chapter 6: Do Criminals Rest on Weekends and Holidays? A Small-Area Bayesian Spatiotemporal Analysis of Crime Patterns

6.1 Introduction

For many people who work or study, weekends and holidays are devoted to rest. However, it is questionable whether potential criminals also rest on weekends and holidays. Do weekends and holidays record lower crime compared to business days? Is the spatial distribution of crime on weekends and holidays different from business days? Do different crime types present various spatiotemporal patterns? Answers to these questions are important to both crime research and crime control. From the perspective of academic studies, investigating the spatiotemporal variation of crime can support the examination and enrichment of criminology theories. From the perspective of law enforcement, understanding when and where crime occurs can assist in the development of proactive policing strategies.

The spatiotemporal distribution of crime is not random. Routine activities theory indicates that a crime occurrence requires a suitable target, a potential offender, and the lack of guardianship to intersect in space and time (Cohen & Felson, 1979). From a theoretical perspective, weekends and holidays should have different crime patterns from business days due to the changes in most people's space of activities (e.g., not going to work). In empirical research, impacts of the day of week or holidays on crime patterns have been frequently considered (e.g., Butke & Sheridan, 2010; Ceccato & Uittenbogaard, 2014; Horrocks & Menclova, 2011). However, limited in-depth research has been conducted to explicitly analyze the distinctive crime patterns on weekends or holidays. In a rare study focusing on the effects of different holidays on different crimes, Cohn and Rotton (2003) performed a temporal analysis in Minneapolis and found that on legal holidays, violent crime incidents increased while property crime incidents decreased, but this research did not include a spatial dimension to the analysis. In one of the few spatiotemporal studies about intra-week crime patterns, Andresen and Malleson (2015) explored multiple crime types in Vancouver using a spatial point pattern test and found that on Saturday, occurrences of assault and theft from vehicle increased in different areas of the city.

This study seeks to contribute to the literature by explicitly investigating the small-area spatiotemporal variation of crime between business days and non-business days in the former municipality of Toronto using Bayesian spatiotemporal modelling. Non-business days are defined as weekends (Saturdays and Sundays) and public holidays in the study area (New Year's Day, Family Day, Good Friday, Victoria Day, Canada Day, Labour Day, Thanksgiving Day, Christmas Day, and Boxing Day). The primary objective of this study is to map the small-area spatiotemporal variation of five major crime types (assault, robbery, auto theft, break and enter, and theft over $5,000) between business days and non-business days. The secondary objective is to explain spatiotemporal patterns using sociodemographic characteristics and characteristics of the built environments across the study area.

6.2 Background

6.2.1 Opportunities for Crime on Business Days and Non-Business Days

Opportunity is recognized to be an important cause of all types of offence (Felson & Clarke, 1998). Routine activities theory is the most popular opportunity theory for crime. According to this theory, changes in routine activities alter the opportunities for offenders, victims and the absence of guardianship to converge, thus affecting crime occurrences (Cohen & Felson, 1979). In line with routine activities theory, crime pattern theory argues that individuals develop awareness space based on their routine activity space, and criminals usually choose targets within their awareness space (Brantingham & Brantingham, 1993). Clarke and Cornish (1985) added a rational choice perspective to opportunity theories, this is, individuals who are ready for offending make their final decisions to commit crimes after subjective considerations of the situational factors.

The aforementioned criminology theories are frequently used to explain the uneven distribution of crime in time and space. From a temporal perspective, more crimes might occur when potential criminals and suitable targets are more likely to share activity space; for example, in summer months when people have more outdoor activities. Such seasonality of crime has been well examined in the literature (e.g., Andresena & Malleson, 2013; Ceccato, 2005; McDowall et al., 2012). The changes in human activities and criminal opportunities also apply to finer temporal scales (e.g., weekdays versus weekends and nighttime versus daytime).

Non-business days are expected to have different human activity patterns from business days. However, it is difficult to simply state whether non-business days would have fewer or more crime occurrences than business days because the changes in criminal opportunities are not spatially homogeneous. Indeed, the spatial and temporal dimensions of crime are inseparable. Crime pattern theory states that offenders usually search for targets around their activity nodes (homes, schools, workplaces, etc.) and the paths between nodes (Brantingham & Brantingham, 1993). Ratcliffe (2006) argues that many activity nodes have temporal constraints, which limit the range of activity space and influence the spatiotemporal patterns of crime. On business days, many people have to stay at work or school for a certain amount of time, which restricts their activities. On non-business days, more people would spend time at home or recreational locations away from work or school. As a result, non-business days may generate more criminal opportunities in residential and recreational areas and fewer criminal opportunities around workplaces and school campuses.

In addition to the spatiotemporal variation of criminal opportunities, the characteristics of different crime types are noteworthy. Some previous studies have identified different spatiotemporal patterns of different crime types (e.g., Andresen and Malleson, 2015; Grubesic & Mack, 2008; Uittenbogaard, & Ceccato, 2012). In the case of business days and non-business days, changes in opportunities for some different types of offences are expected to be dissimilar, even in the same type of space. For example, in residential areas, since more people stay at home on non-business days, opportunities for domestic violence might increase, but opportunities for residential break and enter might decrease due to better guardianship.

6.2.2 Approaches to Analyzing the Spatiotemporal Variation of Crime

Advances in the sizes and forms of crime data have improved the feasibility of spatiotemporal analysis of crime (Newton & Felson, 2015). Most crime data can be categorized as point data or areal data. For point data that records the location and time of each crime occurrence, cluster analysis has been widely applied. Different space-time cluster detection techniques have been developed in the literature and one popular method is the space-time scan test, which uses moving windows with different temporal and geographic extents to detect clusters (Kulldorff et al.

1998). The space-time scan test can be applied to crime analysis at various temporal scales; for example, Uittenbogaard and Ceccato (2012) examined the crime clusters within the day and week as well as the crime seasonality in Stockholm using this technique.

Other methods can be applied to area-based crime data. For crime point data grouped into areas, Andresen (2009) proposes a spatial pattern test to measure the degree of similarity in space between two datasets. This method has been used to compare the spatial patterns of crime of different times and map the locations of significant local differences (Andresen & Malleson, 2013, 2015). Space-time modelling approaches have also been frequently used in crime research. Weisburd et al (2004) present the use of trajectory analysis over multiple time periods, which places areas (street segments in their research) into different groups, each modelled by a unique temporal trajectory of crime. To account for the distinctive spatial and temporal effects in every small area and to analyze the impacts of covariates, regression modelling techniques can be used. For example, Chun (2014) used generalized linear mixed regression to model the spatial and temporal random effects in small census areas over six years in an analysis of vehicle burglary.

In addition to the previously reviewed traditional frequentist methods, Bayesian spatiotemporal modelling has also been applied in recent crime research. While frequentist approaches view parameters as unknown constants, Bayesian approaches model parameters as random variables and provide probability statements about the parameter values (Bolstad & Curran, 2016). In Bayesian spatiotemporal modelling, spatial, temporal, and spatiotemporal terms are assigned appropriate prior distributions, which are updated using Markov Chain Monte Carlo (MCMC) simulation based on the observed data to generate posterior distributions. Different Bayesian spatiotemporal models have been applied to small-area crime analyses in different research contexts (e.g., Law et al., 2014, 2015; Li et al., 2014; Quick et al., 2019).

The use of small spatial units of analysis has become increasingly popular in crime research (Weisburd et al., 2009). The homogeneity of environmental conditions within smaller areas can improve the reliability of analysis outcomes, yet small-area analysis might suffer the small number problem, where small crime counts lead to unstable parameter estimates (Oberwittler & Wikström, 2009). Bayesian approaches are particularly advantageous to small-area studies confronting the small number problem because they allow small areas to borrow information from neighbouring areas to produce stabilized estimates of crime risks (Law et al., 2014).

6.3 Study Area and Data Sources

The study area is the former municipality of Toronto (i.e., Old Toronto), which was amalgamated with five other municipalities into the current City of Toronto in 1998. These older municipality boundaries were adopted, since they encompass a smaller geographic area that is focused on the economic and political core of the city. Old Toronto is important as, (a) an area of concentrated political activity that houses many government buildings and consulates, (b) an economic centre with an important financial district, (c) a transportation hub with major transportation nodes, and (d) a leisure and entertainment destination with various malls, tourist attractions, and sports arenas. Old Toronto is also distinguished as a zone with high employment concentration within the City of Toronto (Toronto City Planning, 2020). Such characteristics of the Old Toronto municipality area are ideal for this study, since it may lead to high population mobility in and out of the area, especially between business days and non-business days. This, in turn, may influence observed crime patterns according to opportunity theories (Felson & Clarke, 1998). The City of Toronto is considered to be a relatively safe major city in the world, but Statistics Canada (2020b) indicates that the crime severity index, which accounts for both the amount and seriousness of police-reported crime, has been continuously increasing in the city. Old Toronto is a crime hot spot in the city according to the preliminary analysis of the crime data.

The spatial unit of analysis is the dissemination area (DA). The DA is the smallest census geographic unit in Canada and a DA usually has a population between 400 and 700 (Statistics Canada, 2018b). Old Toronto contains 1,110 DAs, yet one DA was excluded from the entire study because it does not have spatial neighbours, which are necessary for spatiotemporal modelling. 19 other DAs without complete data to represent sociodemographic characteristics were excluded from the secondary analysis in this study (i.e., the analysis of explanatory variables). Figure 6-1 illustrates the location of Old Toronto within the current City of Toronto boundaries, as well as the corresponding DAs within Old Toronto. The boundary file of Old Toronto was obtained from Toronto Open Data (City of Toronto, 2020a).

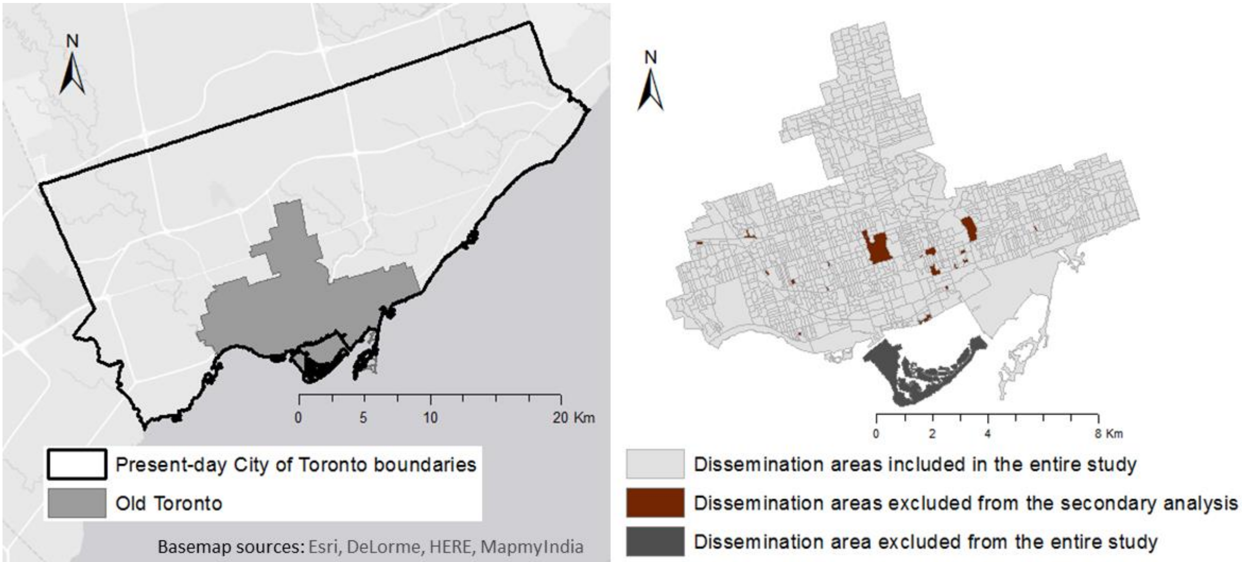


Figure 6-1. Location of Old Toronto in the City of Toronto (left) and DAs within Old Toronto (right, DAs excluded from this study are marked).

DA boundaries are defined based on the 2016 census of Canada, which provides statistics of various themes at different census geographic scales (Statistics Canada, 2020c). Data required for the calculation of sociodemographic variables in the analysis of explanatory variables was also extracted from the census (Statistics Canada, 2020c). Additionally, three built environment datasets, including school locations, park boundaries and business improvement area (BIA) boundaries, were downloaded from Toronto Open Data (City of Toronto, 2020b, 2020c, 2020d).

Crime data used in this study consisted of the major crime indicators data retrieved from Toronto Police Public Safety Data Portal in June 2020 (Toronto Police Service, 2020b). The crime data records the dates and locations of occurrences of five major crime types (assault, robbery, auto theft, break and enter, and theft over $5,000) between 2014 and 2019. For each crime type, crime incidents between 2015 and 2019 were grouped based on their dates and locations to obtain the five-year crime counts on business days and non-business days in each DA within the study area. Table 6-1 shows the descriptive statistics for the crime counts in the 1,109 DAs included in the primary analysis. The crime counts in DAs are generally small with many zero values, which could contribute to the small number problem in statistical modelling.

Table 6-1. Descriptive statistics for crime in the 1,109 DAs included in the primary analysis

Crime type	Mean	Minimum	Maximum	Standard deviation	Number of DAs with 0 count
Business days (1,254 days in total)					
Assault	21.1	0	830	48.3	125
Robbery	3.9	0	94	8.6	445
Auto theft	2.4	0	39	3.4	294
Break and enter	9.0	0	165	12.7	99
Theft over $5,000	1.4	0	65	3.6	576
Non-business days (572 days in total)					
Assault	11.9	0	336	27.4	223
Robbery	2.0	0	57	4.8	592
Auto theft	1.1	0	20	1.9	539
Break and enter	4.0	0	87	6.2	251
Theft over $5,000	0.6	0	29	1.8	800

6.4 Methodology

6.4.1 Bayesian Spatiotemporal Models

As a small-area analysis, this study employed Bayesian modelling to assess the spatiotemporal variation of crime. Methods used in this study were mainly based on Law et al. (2014), who analyzed property crime over two time periods in 1,128 small areas, and Li et al. (2014), who investigated burglary risks over four time periods in 452 small areas.

For each crime type, the crime count in each DA was modelled using a Poisson distribution:

$$O_{it} \sim Poisson(n_t \mu_{it}), \tag{6-1}$$

where O_{it} is the five-year (2015-2019) crime count in DA i during time period t ($t = 1$ represents business days and $t = 2$ represents non-business days), n_t is the number of days in time period t ($n_1 = 1{,}254$; $n_2 = 572$); and μ_i is the daily crime risk in area i. Both crime counts and crime rates have been used in previous crime research. This study used crime counts because no population datasets in the study area account for the population mobility between business days and non-business days.

The daily crime risk in area i (μ_{it}) was represented by the equation below:

$$\mu_{it} = \alpha + (S_i + U_i) + b_0 T_t + b_i T_t, \tag{6-2}$$

where α is the mean crime risk; S_i and U_i are the structured spatial effect and the unstructured spatial effect, respectively; b_0 and b_i are the mean temporal term and the area-specific temporal term (i.e., spatiotemporal interaction term), respectively. T_t is t centring at the middle point (i.e., $T_t = t - 0.5$). This allows the sum of S_i and U_i to represent the average area-specific crime risks between the two time periods.

To account for the impacts of some sociodemographic characteristics and built environments, Equation 6-2 was extended to develop a second model:

$$\mu_{it} = \alpha + (S_i + U_i + \beta 1 \cdot X1_i) + b_0 T_t + (b_i + \beta 2 \cdot X2_i) T_t, \tag{6-3}$$

where $\beta 1 \cdot X1_i$ and $\beta 2 \cdot X2_i$ are included to explain some of the spatial variation and local temporal patterns, respectively. $X1_i$ and $X2_i$ each is a column vector recording the values of a series of explanatory variables in area i; $\beta 1$ and $\beta 2$ represent row vectors of regression coefficients associated with $X1$ and $X2$, respectively. To improve convergence, each explanatory variable was centred at the mean.

Vague prior distributions were assigned to the model parameters in this study due to the lack of prior knowledge. α was given a uniform distribution. b_0 and the regression coefficients in $\beta 1$ and $\beta 2$ were each given a normal distribution with the mean equal to 0 and the variance equal to 1000. U_i was given a normal distribution with the mean equal to 0 and the variance equal to σ_u^2. S_i and b_i were each modelled based on an intrinsic conditional autoregressive (ICAR) prior (Besag et al, 1991). In the ICAR model, S_i and b_i are each normally distributed with the mean dependent on the spatially neighbouring values (spatial neighbours are classified as DAs that share at least one edge or vertex) and the variance for S_i and b_i are equal to σ_s^2/n_i and σ_b^2/n_i, respectively (n_i is the number of neighbouring DAs to DA i). Such prior settings for S_i and b_i in small-area modelling allow neighbouring areas to present similar spatial and temporal patterns, which deals with the small number problem, the spatial clustering of crime, and misplaced crime incidents between neighbouring areas (Law et al., 2014). The variance terms (σ_u^2, σ_s^2 and σ_b^2) were each modelled in a commonly used distribution of $Gamma(0.5{,}0.0005)$.

6.4.2 Explanatory Variables

In the second Bayesian model (Equation 6-3), eight sociodemographic variables and three built-environment variables were included as explanatory variables for the spatial variation of crime ($X1$). The three built environment variables were also used as explanatory variables for the temporal variation of crime ($X2$). Descriptive statistics for the explanatory variables are shown in Table 6-2.

Table 6-2. Descriptive statistics for explanatory variables based on sociodemographic and built environment characteristics

Sociodemographic variables (spatial explanatory variables)				
Variable	**Mean**	**Minimum**	**Maximum**	**Standard deviation**
% low income	16.8	0.0	78.9	11.6
% movers	42.8	5.9	97.9	15.3
Ethnic fractionalization (0-100)	45.7	3.8	84.4	17.7
% no post-secondary degrees	23.3	0.0	73.8	13.8
Gini coefficient (0-100)	40.2	10.0	70.4	7.5
% richer than the poorest neighbour	70.0	-71.9	632.2	85.1
Census population (hundred)	7.3	2.6	79.4	6.2
Census population density	13.3	0.1	118.5	13.0
Built environment variables (spatial and temporal explanatory variables)				
Variable (binary)	**Number of 0s**		**Number of 1s**	
Schools	255		885	
Parks	27		1063	
Business improvement areas	596		494	

As described in Section 6.4.1, the census population is not an appropriate measure of the at-risk population to calculate crime rates in this study, yet it is still expected to influence crime counts. Therefore, population count and population density were included as spatial explanatory variables. Other spatial explanatory variables were selected based on criminology theories. For example, social disorganization theory links the concentration of crime in space to community characteristics that lead to weaker social control (Shaw & Mckay, 1942). Previous research has examined the effects of various community characteristics on increasing crime rates, including poverty, income inequality, residential instability, ethnic heterogeneity and low education attainment (Bursik & Grasmick, 1999; Elliot et al., 1996; Hipp, 2007; Sampson & Groves, 1989). To account for these factors in this study, % low income (percent of low-income residents), % movers (percent of the residents that moved within the past five years), ethnic fractionalization, and % no post-secondary degrees (percent of the residents aged 25+ without post-secondary degrees) were used to quantify poverty, residential instability, ethnic heterogeneity and low education attainment, respectively. Ethnic fractionalization is given by Equation 6-4 below:

$$\text{Ethnic fractionalization} = (1 - \sum \pi_i^2) \times 100\% \qquad (6\text{-}4)$$

where π_i is the proportion of residents that identify themselves in ethnic group i.

Income inequality was represented by two variables, the Gini coefficient and % richer than the poorest neighbour. The Gini coefficient measures income inequality within each DA by quantifying the deviation of the observed income distribution from an equal distribution, while a larger Gini value indicates a higher level of income inequality. Developed based on Metz and Burdina (2018), % richer than the poorest neighbour measures the disparities in the median incomes between neighbouring DAs and it is given by Equation 6-5 below:

$$\%\ \text{richer than the poorest neighbour} = \frac{Inc - MinNeiInc}{MinNeiInc} \times 100\%, \qquad (6\text{-}5)$$

where Inc is the median after-tax household income in an area and $MinNeiInc$ is the minimum median after-tax household income in its spatially neighbouring areas.

In order to assess temporal variation, this study considers three types of built environments that may generate different routine activity patterns between business days and non-business days: schools, parks (green spaces), and business areas (represented by BIAs). Schools tend to be busier on business days while parks may have more visitors on non-business days. Some business areas may be busier on weekends and holidays while others may be less busy due to the closure of some businesses. For each built environment type, a binary variable was used, this is, DAs with the built environment were assigned a value of one and all other DAs were assigned a value of zero. These built environments are also considered to be crime generators according to the crime pattern theory because they are locations with a large concentration of human activities (Brantingham & Brantingham, 1993). Therefore, the three built environments were also included as spatial explanatory variables in the models.

6.5 Results

Bayesian models were implemented in WinBUGS, a statistical software tool that generates posterior distributions of model parameters using the MCMC method (Spiegelhalter et al., 2003). WinBUGS code for the second model (Equation 6-3) is provided in Appendix E. For each model and each crime type, two parallel MCMC chains with different initial values were run. Convergence was reached after 50,000 iterations. Posterior statistics were obtained from running an additional 50,000 iterations. The Monte Carlo error for every parameter was smaller than 5% of the corresponding posterior standard deviation, which indicated that adequate samples have been collected to generate the posterior distributions (Spiegelhalter et al., 2003). As previously stated, spatiotemporal patterns of crime were obtained from the first model (Equation 6-2) with 1,109 DAs while results of explanatory variables were obtained from the second model (Equation 6-3) with 1,090 DAs due to the lack of data to quantify socioeconomic variables in 19 DAs. The first model was also tested on the 1,090 DAs and the exclusion of the 19 DAs did not have significant impacts on the results of other DAs.

6.5.1 Overall and Local Temporal Patterns

Results in this section were obtained from the first model. Table 6-3 shows the posterior mean and 95% credible interval (CI) of the mean temporal term (b_0) of each crime type. The mean temporal terms of assault and robbery are positive at 95% CIs, indicating non-business days have significantly higher risks of crime compared to business days for these two crime types. Non-business days may also be associated with higher risks of auto theft and lower risks of break and enter and theft over $5,000 compared to business days, but these changes are not significant at 95% CIs.

Table 6-3. Mean temporal patterns between business days and non-business days

Crime type	**Assault**	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
$\boldsymbol{b_0}$ **(95 % CI)**	0.165 (0.127,0.202)	0.0901 (0.0149,0.165)	0.0452 (-0.0251,0.115)	-0.0355 (-0.0751,0.00352)	-0.0591 (-0.153,0.0332)

Maps of local temporal patterns are shown in Figures 6-2 to 6-6. The local temporal change in a DA is considered to be the sum of the mean temporal term (b_0) and the area-specific temporal term (b_i). For each crime type in each DA, the posterior mean of local temporal change is used to represent the magnitude of the change in crime risk between business days and non-business days, and the posterior probability that the local temporal change is positive is used to represent the significance of the temporal change. A posterior probability close to one indicates a significantly positive temporal change, meaning that the DA has a higher crime risk on non-business days compared to business days. A posterior probability close to zero implies a high probability that the local temporal change is negative, thus indicating that the DA has a lower crime risk on non-business days compared to business days.

DAs that are associated with higher risks of assault on non-business days compared to business days (Figure 6-2) are mainly identified in the south of the Old Toronto area, especially around the shoreline. DAs with higher risks of robbery on non-business days compared to business days (Figure 6-3) are noticeably found in the southern and central-northeastern regions of the study area. DAs with lower risks of these two violent types of crime on non-business days compared to business days are randomly dispersed across the rest of the study area. For auto theft (Figure 6-4) and break and enter (Figure 6-5), clustering of DAs with lower crime risks on non-business days compared to business days are markedly located towards the north. In contrast, clusters of DAs with higher risks of auto theft on non-business days compared to business days are found in the eastern and central-southwestern regions of the study area. For the local temporal patterns of break and enter, no posterior means of local temporal changes are greater than 0.1 and no posterior probabilities of positive local temporal changes are greater than 0.8, meaning that no DA has significantly higher risks of break and enter on non-business days compared to business days. Theft over $5,000 (Figure 6-6) presents some unique patterns of local temporal changes. Every posterior mean is between -0.1 and 0, indicating that every DA tends to have a slightly lower risk of theft over $5,000 on non-business days compared to business days. Such small magnitudes of changes may be due to the extremely small crime counts of this crime type (see Table 6-1 in Section 6.3). In terms of the significance of local temporal patterns, both the west and east show less significant changes (posterior probabilities between 0.2 and 0.3), while the rest of the study area shows more significant changes (posterior probabilities between 0.1 and 0.2).

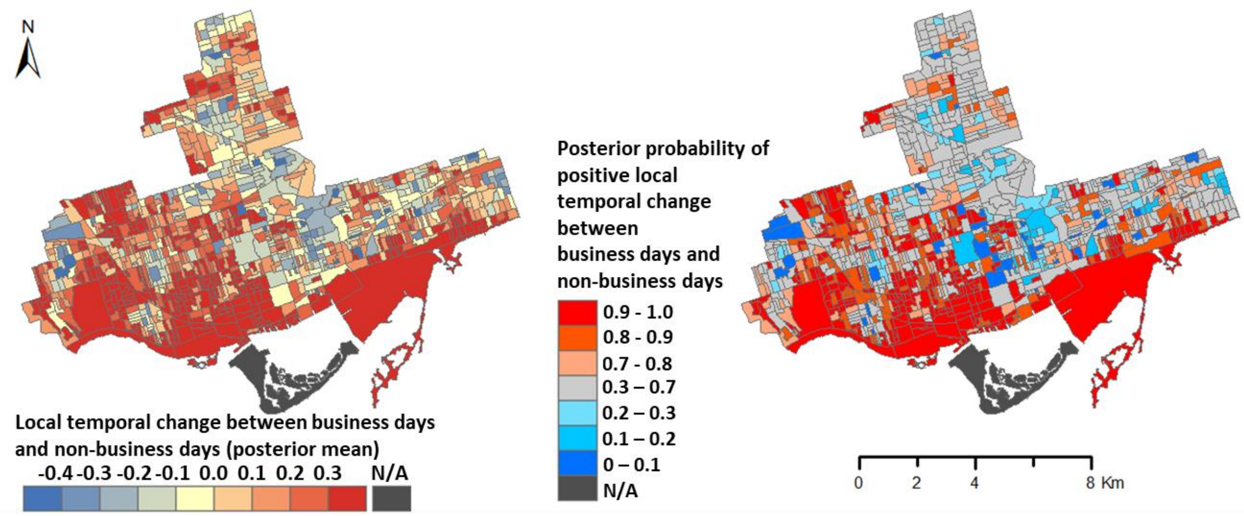


Figure 6-2. Local temporal patterns of assault: posterior means of local temporal changes (left) and posterior probabilities of positive local temporal changes (right).

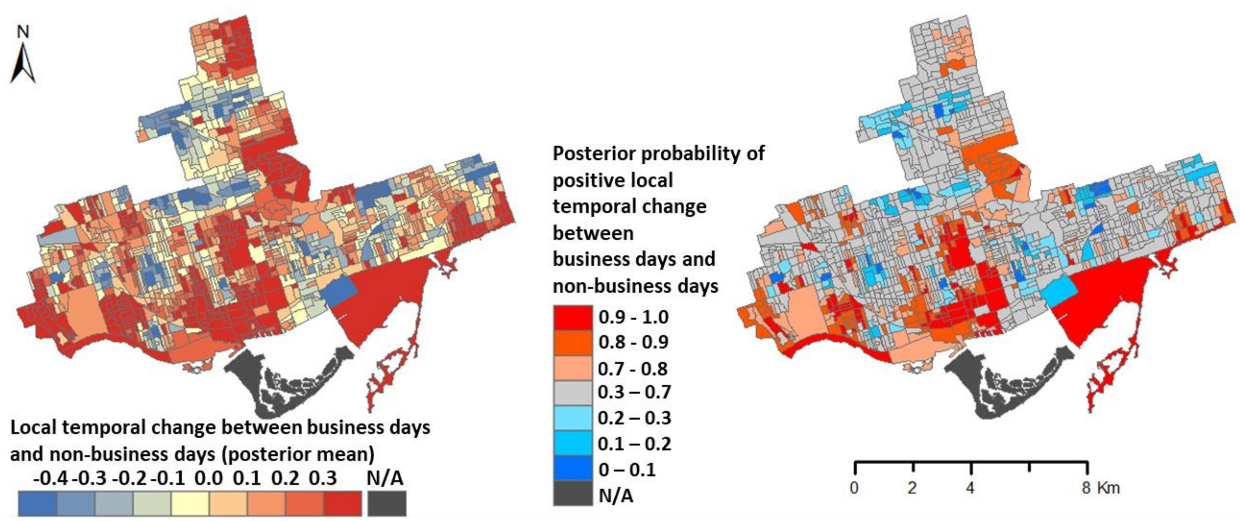


Figure 6-3. Local temporal patterns of robbery: posterior means of local temporal changes (left) and posterior probabilities of positive local temporal changes (right).

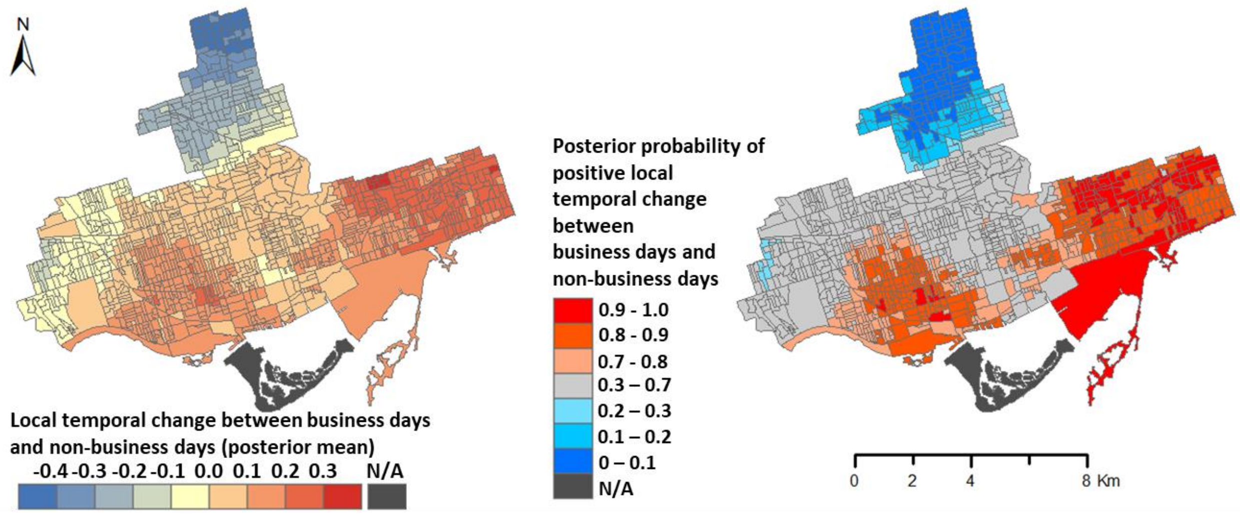


Figure 6-4. Local temporal patterns of auto theft: posterior means of local temporal changes (left) and posterior probabilities of positive local temporal changes (right).

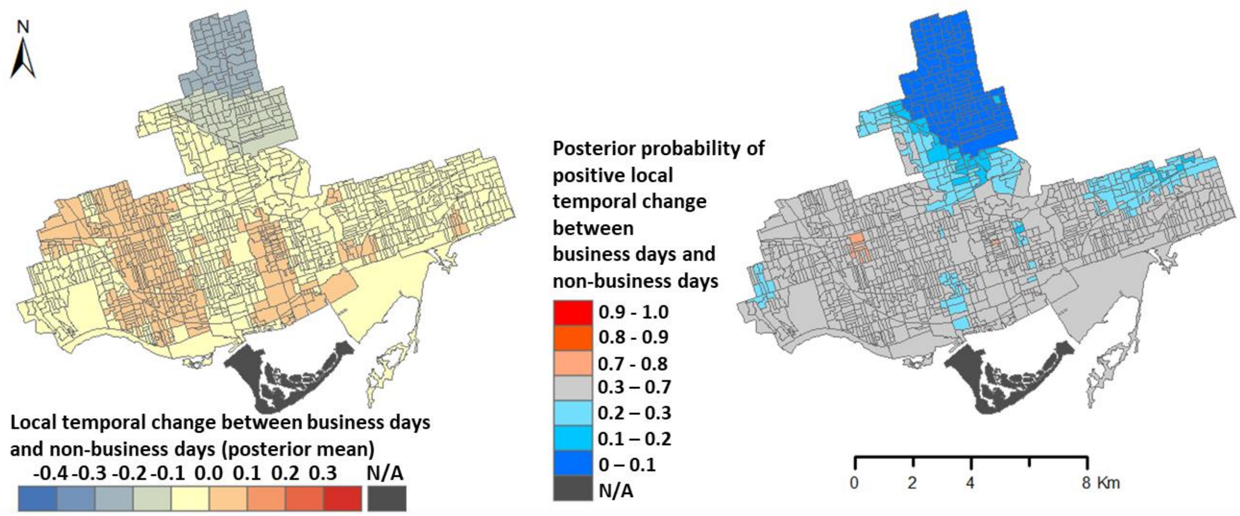


Figure 6-5. Local temporal patterns of break and enter: posterior means of local temporal changes (left) and posterior probabilities of positive local temporal changes (right).

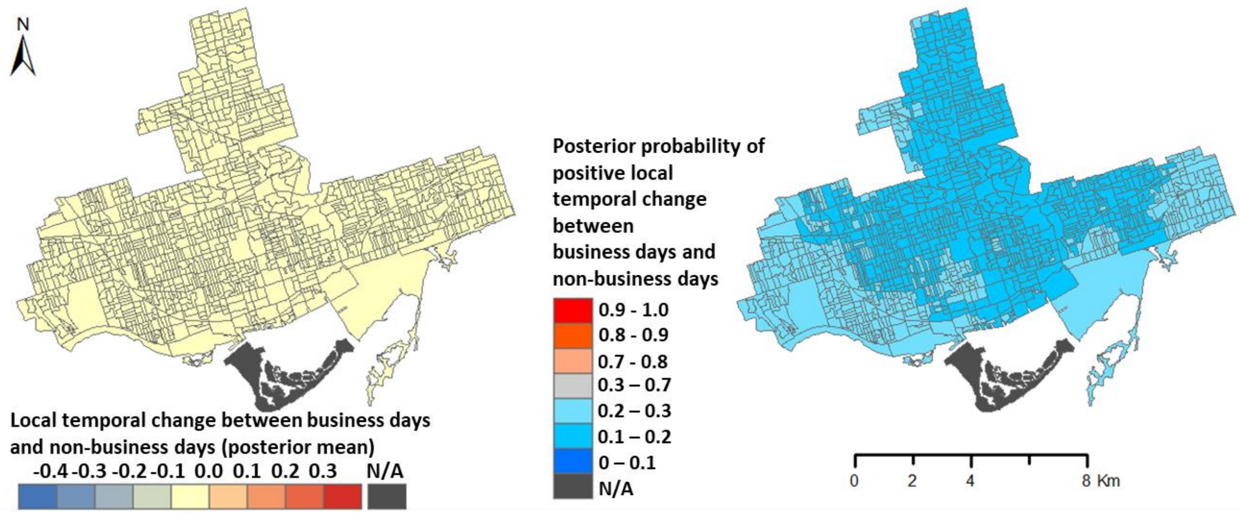


Figure 6-6. Local temporal patterns of theft over $5,000: posterior means of local temporal changes (left) and posterior probabilities of positive local temporal changes (right).

6.5.2 Spatial Effects and Hot Spot Patterns

For effective crime control, it is important to be aware of the spatial distribution of crime and the areas with significantly higher crime risks than other areas (i.e., crime hot spots). Based on the first model, local spatial risks are represented by the spatial relative risk ($e^{S_i+U_i}$) in each DA, which indicates how many times the local crime risk is as high as the mean crime risk in the study area. Hot spots in each time periods are defined based on the difference between the local crime risk and the mean risk, which is given by the sum of the area-specific spatial effect ($S_i + U_i$) and the area-specific temporal effect ($b_i T_t$). A DA is considered to be a hot spot in time period t if its posterior probability of positive ($S_i + U_i + b_i T_t$) is greater than 0.8. Persistent hot spots (i.e., DAs that are hot spots on both business days and non-business days) are further categorized based on the posterior probabilities that the local temporal change ($b_0 + b_i$) is positive (the same posterior probabilities used in Section 6.5.1). Probabilities less than 0.2 and greater than 0.8 indicate significantly negative local temporal changes (i.e., the crime risks are higher on business days) and significantly positive local temporal changes (i.e., the crime risks are higher on non-business days), respectively. The significance filters of 0.2 and 0.8 and the cross-classification method of spatial and temporal patterns were presented in Li et al. (2014), but they analyzed spatial and temporal hot spots based on the average spatial effect during the study period ($S_i + U_i$) and the relative temporal change to the mean temporal change (b_i). In contrast, this study is concerned with the changes in hot spot locations and the absolute temporal changes within persistent hot spot areas. Figures 6-7 to 6-11 show the spatial relative risks and the hot spot patterns of the five types of crime.

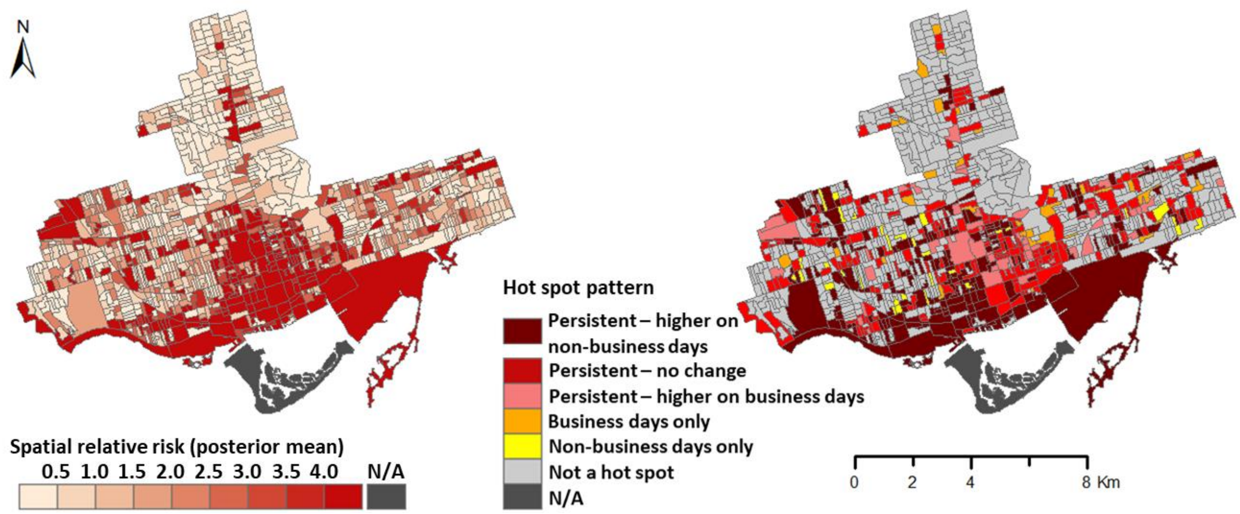


Figure 6-7. Spatial relative risks (left) and hot spot patterns (right) of assault.

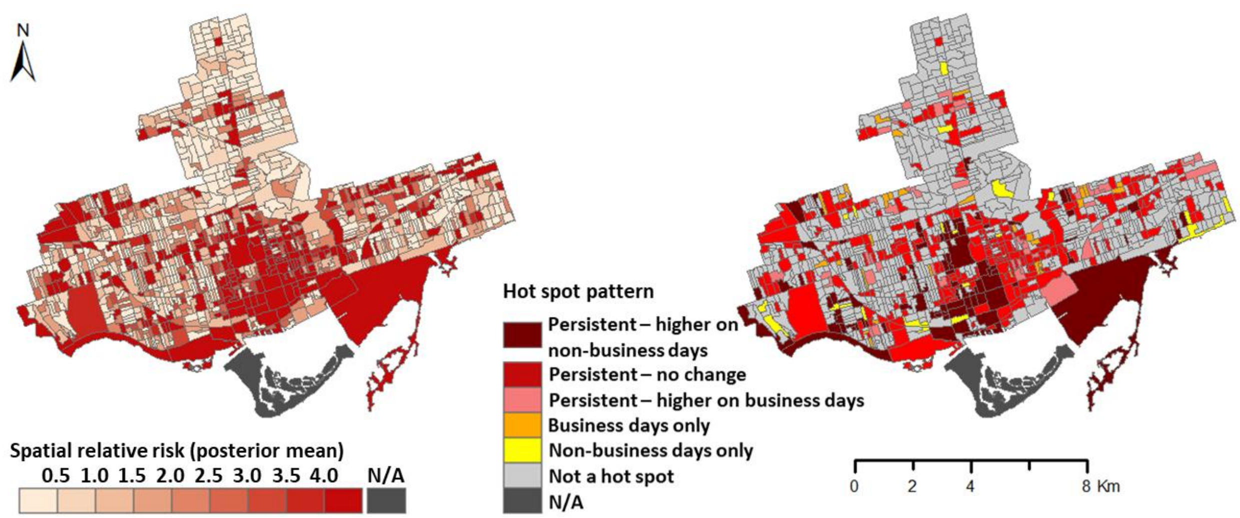


Figure 6-8. Spatial relative risks (left) and hot spot patterns (right) of robbery.

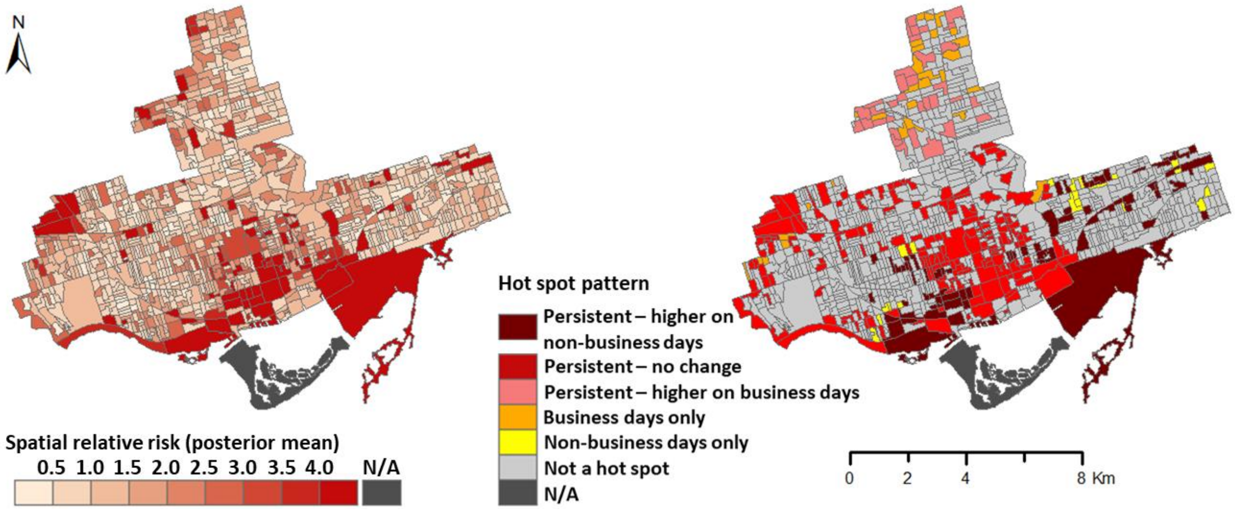


Figure 6-9. Spatial relative risks (left) and hot spot patterns (right) of auto theft.

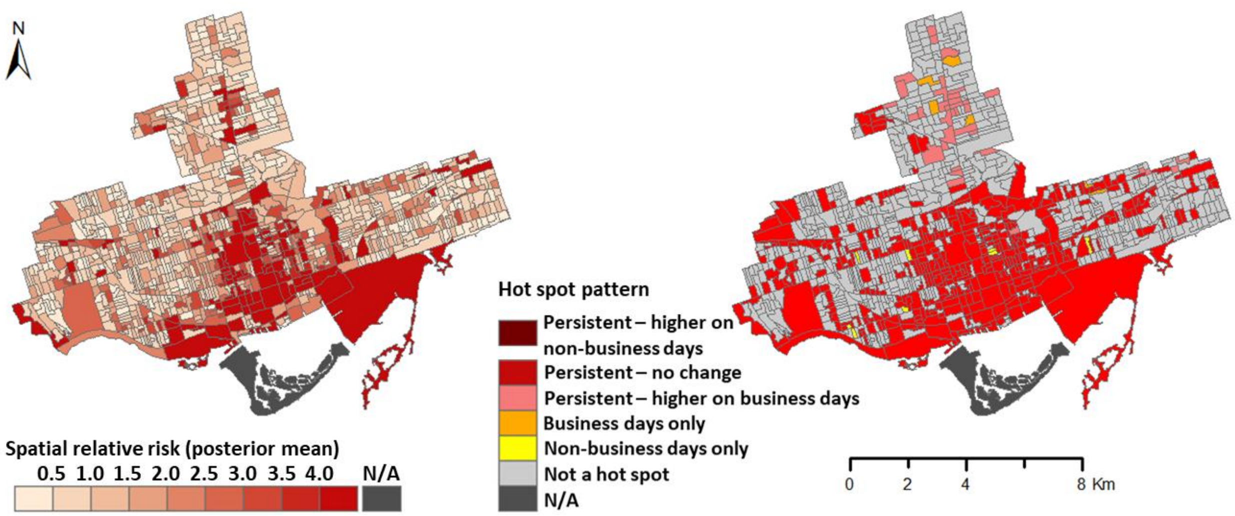


Figure 6-10. Spatial relative risks (left) and hot spot patterns (right) of break and enter.

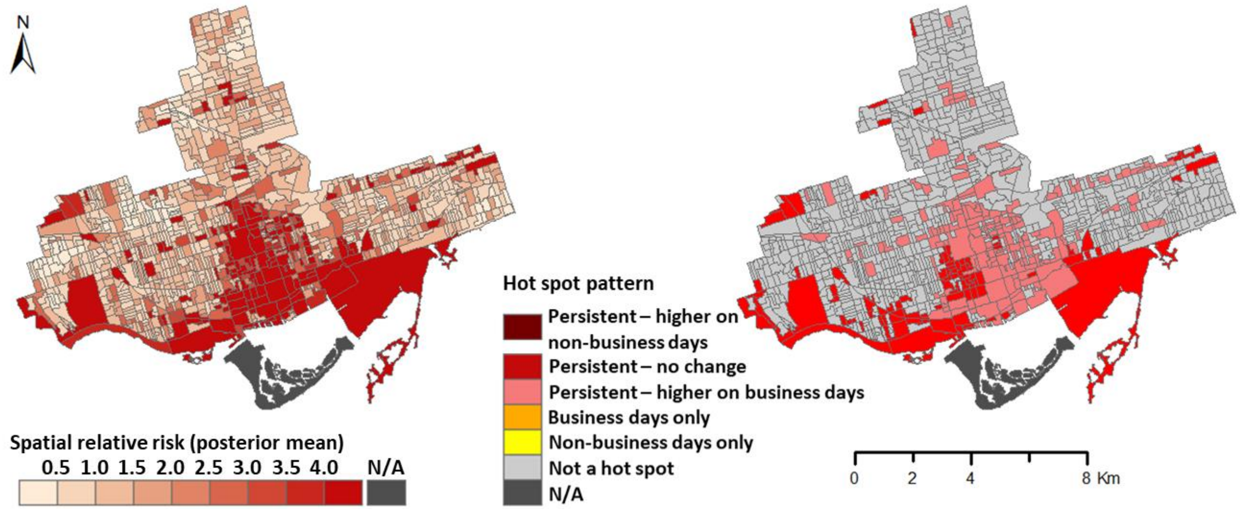


Figure 6-11. Spatial relative risks (left) and hot spot patterns (right) of theft over $5,000.

For assault (Figure 6-7), crime hot spots are mainly located in the south and the core of the northern region of the study area. Many southern hot spots are found within downtown Toronto or along the shoreline areas, while many northern hot spots are found around Yonge Street (see Section 6.6.1 for further discussion). Noticeable clusters of persistent hot spots that show higher crime risks on non-business days compared to business days are identified along the shoreline areas. Some persistent hot spots in the downtown area exhibit lower crime risks on non-business days compared to business days. Hot spots in only one time period are dispersed across the study area and mostly adjacent to the persistent hot spots. Robbery hot spots (Figure 6-8) are similarly distributed as those of assault, but persistent hot spots that show higher crime risks on non-business days compared to business days are mainly clustered in the downtown area. For auto theft (Figure 6-9), persistent hot spots with higher crime risks on non-business days compared to business days and hot spots only on non-business days are mostly found in the central-southwestern and eastern regions of the study area. The north contains some persistent hot spots that show lower crime risks on non-business days compared to business days and hot spots only on business days. Persistent hot spots without significant local temporal changes are located in the downtown area and around the western boundary region. For break and enter (Figure 6-10), most persistent hot spots in the south have no significant local temporal changes and persistent hot spots that exhibit lower crime risks on non-business days compared to business days are markedly identified along the middle line of the north (Yonge Street). A few hot spots only on business days and only on non-business days are found in the north and south, respectively. For theft over $5,000 (Figure 6-11), hot spot locations are mainly in the downtown area and around the shoreline. All hot spots are persistent and many hot spots in the middle show lower crime risks on non-business days compared to business days.

6.5.3 Regression Coefficients

Table 6-4 shows the means and 95% CIs of the regression coefficients obtained from the second model (Equation 6-3) in the form of relative risks (i.e., the exponential transformation of the regression coefficients). Relative risks greater than one indicate positive associations; relative risks less than one indicate negative associations. In the spatial explanatory variables, % richer than the poorest neighbour, % low income, % movers, population count, parks and BIAs are found to be positively associated with all crime types at 95% CIs. The positive impacts of ethnic fractionalization on assault and robbery are also significant at 95% CIs. The Gini coefficient is negatively associated with auto theft at the 95% CI. Population density is negatively associated with all crime types at 95% CIs. As for the temporal effects of the built environment variables, schools are negatively associated with the local temporal changes of assault at the 95% CI. Such impacts of schools may also apply to robbery, but the CI (0.737, 1.039) is larger, and the right end of the CI is slightly above one. Parks are positively associated with the local temporal changes of theft over $5,000 at the 95% CI, BIAs might have some positive impacts on the local temporal changes of break and enter with borderline significance as the left end of the 95% CI (0.994, 1.174) is slightly below one.

Table 6-4. Regression coefficients of the explanatory variables (posterior means and 95% CIs of the relative risks)

	Assault	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Spatial explanatory variables					
% low income	1.02 (1.01,1.031)	1.029 (1.014,1.043)	1.015 (1.007,1.024)	1.012 (1.004,1.021)	1.015 (1.003,1.027)
% movers	1.018 (1.012,1.025)	1.014 (1.005,1.023)	1.009 (1.003,1.014)	1.013 (1.007,1.018)	1.019 (1.012,1.026)
Ethnic fractionalization	1.017 (1.01,1.023)	1.01 (1.001,1.019)	1.002 (0.997,1.007)	1.004 (0.999,1.009)	1.004 (0.997,1.012)
% no post-secondary degree	1.004 (0.995,1.014)	1.000 (0.988,1.012)	0.998 (0.99,1.005)	0.998 (0.991,1.005)	0.998 (0.988,1.008)
Gini coefficient	1.005 (0.994,1.018)	0.997 (0.982,1.012)	0.986 (0.977,0.995)	1.004 (0.995,1.013)	1.003 (0.99,1.016)
% richer than the poorest neighbour	1.002 (1.001,1.003)	1.003 (1.001,1.004)	1.002 (1.001,1.002)	1.002 (1.001,1.002)	1.001 (1,1.003)
Population count	1.054 (1.036,1.069)	1.047 (1.028,1.065)	1.049 (1.037,1.06)	1.053 (1.041,1.065)	1.055 (1.04,1.069)
Population density	0.966 (0.959,0.976)	0.961 (0.95,0.972)	0.964 (0.957,0.971)	0.971 (0.964,0.977)	0.961 (0.952,0.97)
Schools	1.136 (0.947,1.358)	1.045 (0.826,1.324)	1.007 (0.865,1.172)	1.096 (0.951,1.266)	1.009 (0.821,1.237)
Parks	1.209 (1.01,1.433)	1.254 (1.017,1.55)	1.155 (1.013,1.317)	1.176 (1.039,1.329)	1.256 (1.049,1.503)
BIAs	1.504 (1.27,1.796)	1.734 (1.398,2.151)	1.204 (1.049,1.381)	1.452 (1.278,1.647)	1.448 (1.193,1.76)
Temporal explanatory variables					
Schools	0.859 (0.784,0.941)	0.875 (0.737,1.039)	1.024 (0.865,1.212)	0.948 (0.869,1.032)	1.017 (0.822,1.257)
Parks	1.001 (0.921,1.087)	0.925 (0.795,1.077)	0.913 (0.792,1.053)	1.03 (0.956,1.109)	1.286 (1.064,1.557)
BIAs	0.999 (0.91,1.099)	0.971 (0.82,1.15)	0.953 (0.817,1.109)	1.08 (0.994,1.174)	0.946 (0.761,1.178)

6.6 Discussion

6.6.1 Spatiotemporal Patterns of Major Crimes in Old Toronto

Spatiotemporal patterns of five major crime types between business days and non-business days in the Old Toronto area were investigated, and several key findings are noteworthy. First, some similarities are found in the spatial patterns of different crime types and three zones associated with high crime risks are particularly noticeable. These are areas in the south corresponding roughly with downtown Toronto, which are associated with many businesses and attractions, as well as three universities. Northern areas that match the surrounding areas of Yonge Street were also identified, which corresponding with a major arterial route with heavy traffic and areas of high business activity. Locations of these areas are shown in Figure 6-12. Last, the Lakeshore area was also associated with high crime risk, which corresponds to various recreational land uses, including parks, entertainment destinations, and tourist attractions. The observed high crime risks in these areas with much shared activity space are consistent with opportunity theories.

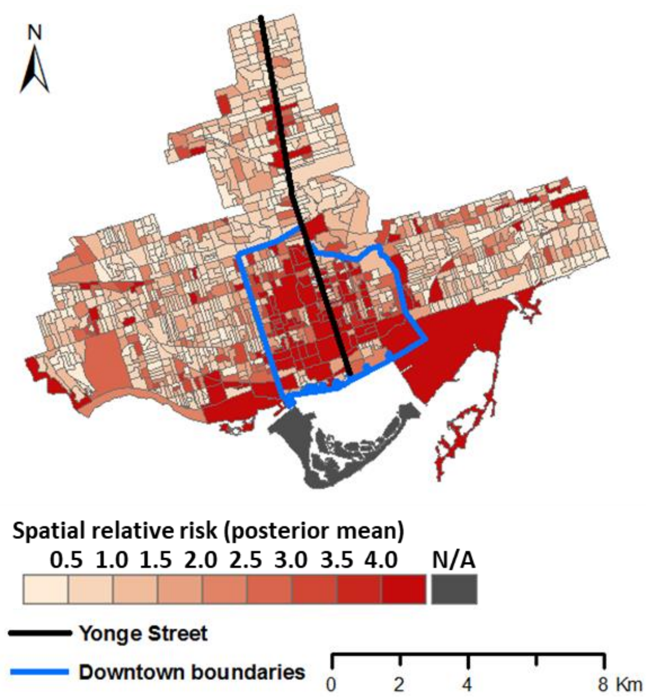


Figure 6-12. Locations of downtown Toronto boundaries and Yonge Street (overlaid on the map of the spatial relative risks of break and enter).

Second, different crime types present various local temporal patterns, but some similarities can be found between violent and property crime types. For violent crime types (assault and robbery), DAs close to the shoreline are associated with higher crime risks on non-business days compared to business days. The recreational land uses in these areas may attract more people on non-business days (weekends and holidays) and produce more crime opportunities. For property crime types (auto theft, break and enter, and theft over $5,000), the north demonstrates lower crime risks on non-business days compared to business days. The northern part of the study area consists mostly of residential land use and contains fewer businesses or recreational areas compared to the south. This area of predominantly residential neighbourhoods may result in less shared activity space and better guardianship of personal property on non-business days when more people stay at home. Many DAs in the south also have lower risks of theft over $5,000 on non-business days compared to business days, but such patterns are not found with the other two property crime types. For break and enter, this might be influenced by the businesses in the south, which could lead to more commercial break and enter on non-business days (see Section 6.6.2 for more discussion). For auto theft, higher risks on non-business days compared to business days are found in the south, which may be related to activities associated with leisure and entertainment locations.

Last, the hot spot maps derived in this study show that most crime hot spots are consistent in both time periods (i.e., categorized as persistent hot spots). Only a small number of DAs are categorized as hot spots in only one time period and most of these DAs are in close proximity to the persistent hot spots. This implies that areas with high crime risks tend to be stable and do not change between business days and non-business days. Nevertheless, for crime control and prevention on non-business days, a number of hot spots, mostly located in southern regions, are associated with higher crime risks of assault, robbery, or auto theft compared to business days, and hence require more attention and crime control measures.

6.6.2 The Effects of Sociodemographic Characteristics and Built Environments

Sociodemographic characteristics that have significant impacts on the spatial patterns of crime have been identified via the second spatiotemporal model developed in this study. In a broader sense, poverty and residential instability tend to increase the risks of all crime types, while ethnic heterogeneity significantly increases violent crime risks, in particular. For income inequality, across-DA income disparity is a more significant risk factor compared to within-DA income inequality in this study, and DAs with higher income levels than their neighbours would attract more criminals. For the population factor, larger populations tend to lead to higher crime risks as expected, while higher residential population densities tend to decrease the crime risks. The impacts of population density have been attributed to the deterrence effects in populated areas and the population mobility from unsafe areas to safer areas, as shown in previous research (Metz & Burdina, 2018; Morenoff et al., 2001; Patino et al., 2014).

In terms of the urban built environments, BIAs and parks are identified as crime generators for all crime types. While for temporal effects, the presence of schools is associated with lower risks of violent crimes on non-business days compared to business days. This is a reasonable conclusion, since most schools are closed on non-business days, which may lead to fewer opportunities for violence to occur around school grounds. The presence of parks is associated with higher risks of theft over $5,000 on non-business days compared to business days. Parks generally see more visitors on non-business days when more people have leisure time, which may increase the chance for potential thieves to encounter suitable victims or the presence of unguarded property around parks. Locations of BIAs are associated with higher risk of break and enter on non-business days compared to business days. This could be the result of more visitor activities around BIAs and the lack of guardianship of the businesses that close on non-business days. This association is also supported by the observed difference in commercial break and enter occurrences between the two time periods. The crime data categorizes break and enter based on five premise types: apartment, house, commercial, outside and other. During business days in the time period of this study, around 2.98 incidents of commercial break and enter occurred per day, which constituted around 14% of all break and enter occurrences. On non-business days, the occurrences per day of commercial break and enter and its proportion in all break and enter increased to 3.13 and 18%, respectively.

6.6.3 Limitations and Future Directions

This research has several limitations. First, Fridays, Saturdays, and public holidays were simply grouped into a category of “non-business days”. In addition to these non-business days that apply to most individuals, holidays for certain groups of people (e.g., students’ summer break) or times on business days that are associated with non-business days (e.g., Friday nights are associated with weekends) may also significantly affect crime patterns. Moreover, this temporal classification scheme may overlook the variation in activities within non-business days; for example, more people tend to go on vacation around public holidays or long weekends than on ordinary weekends. Future research could potentially categorize crime occurrences based on more temporal criteria to analyze the spatiotemporal variation in further detail. However, this may require datasets that have more crime incidents recorded in each area, otherwise a larger spatial unit of analysis should be applied to avoid too many zero crime counts in small spatiotemporal groups, which would limit the analysis.

Second, the quantification and validity of available crime data is recognized to be flawed. Official police-reported data was used in this study, which may omit a considerable proportion of crimes actually occurring in the study area due to low reporting rates (Moreau, 2019). Crime counts instead of crime rates were used due to the unavailability of appropriate datasets to quantify different at-risk populations on business days and non-business days. Future research could consider other quantification methods of crime if additional datasets are available, such as from victimization surveys. Moreover, certain crime types could be further categorized. For example, the results have indicated possibly different patterns between residential and commercial break and enter. Again, trade-offs between small spatial and temporal units will be needed to limit the number of zero crime counts when more subgroups of crime are applied.

Third, only three temporal explanatory variables are considered in this study. The sociodemographic variables and several other built environment variables were eliminated from the temporal explanatory variables in the testing process because no significant impacts were found. Future studies could identify more factors that could potentially affect the temporal variation of crime (e.g., eating and drinking establishments). Furthermore, the three binary variables of built environments used in this research might not accurately represent the changes in population activities between business days and non-business days since they do not reflect the geographic scales as well as the volumes of visitors. Future research could develop other quantifications of built environments (e.g., indicators that account for the location and land area of the built environments) or find data that directly reflect population activities (e.g., foot traffic in shops).

Finally, it is worth noting that this study used only one modelling approach applied to one study area at one spatial scale of analysis. Other statistical models (e.g., frequentist models) could yield different results. The study area, Old Toronto is the heart of a metropolitan area with high population density and mobility and hence the findings in this study area may not be generalizable or applicable to other geographical areas and different urban contexts. Moreover, due to the modifiable areal unit problem (MAUP), which indicates that different data aggregation units can lead to different parameter estimates, analytical outcomes of the same models may differ when applied at other spatial scales (Fotheringham & Wong, 1991; Openshaw, 1984).

6.7 Conclusions

This study applied a Bayesian modelling approach to investigate the spatiotemporal variation of assault, robbery, auto theft, break and enter, and theft over $5,000 in the Old Toronto area. The results have shown some significant spatiotemporal patterns and differences between business days and non-business days, which may have implications for crime prevention practices. First, focusing on the overall temporal changes of crime in Old Toronto, it was noted that the risks of violent crimes (assault and robbery) are higher on non-business days compared to business days. This suggests that more violence control measures, such as police patrol and neighbourhood watch, may be required on non-business days. Second, the local temporal patterns of each crime type vary across space, indicating which days are more vulnerable in each zone. Areas close to the shoreline or harbourfront of Toronto tend to be associated with higher risks of violent crimes (assault and robbery) on non-business days compared to business days, while areas in the north tend to have lower risks of property crimes (auto theft, break and enter, and theft over $5,000) on non-business days compared to business days. Lower risk of theft over $5,000 and higher risks of auto theft on non-business days compared to business days are also located in areas in the south. The presence of schools tends to lead to higher violent crime risks on business days compared to non-business days while the presence of parks and BIAs are associated with higher risks of theft over $5,000 and break and enter, respectively, on non-business days compared to business days. Although some significant local temporal patterns were noted, the hot spots are generally the same on business and non-business days, and adverse community characteristics and crime generating locations (BIAs and parks) tend to be positively associated with local crime risks. The spatial patterns of crime highlight downtown areas, areas surrounding Yonge Street, and areas close to the shoreline or harbourfront as requiring more crime prevention and control measures.

Do criminals rest on weekends and holidays? Instead of a simple "yes" or "no", the answer to this question should be based on the types of crime and the locations of interest being considered. The findings of this study indicate that the temporal patterns between business days and non-business days are different for various categories of crime. Moreover, local temporal patterns in small areas can differ from the temporal pattern of the overall study region and they are affected by characteristics of the built environment. The spatiotemporal approach presented in this research can be applied to any region with appropriate crime data available to assess when, where, and what type of crimes commonly occur. These results provide important information for relevant police and planning authorities, which are seeking to implement effective crime control measures, especially on weekends and holiday periods. Gaining a better understanding of the spatiotemporal patterns of crime enables police departments and crime analysts to better determine the number of officers to hire and deploy within police forces and the ability to adjust patrol plans according to different days of the week, months, and times of the year. Additionally, by distinguishing between the spatiotemporal patterns of various crime types (e.g., violent versus property), different crime prevention measures can be applied in different areas of the city accordingly. For example, an area with increasing occurrences of robbery and an area with increasing occurrences of commercial break and enter may require higher patrol frequencies and more video surveillance, respectively.

Chapter 7: Conclusions

This research applied multiple spatial and spatiotemporal analysis approaches to the data of income inequality and crime at the small area level in the City of Toronto. The three manuscripts in this thesis each achieved distinct research goals, while together contributed to understanding the spatial patterns of income inequality and crime individually, as well as the links between these two important social issues. To conclude this thesis, this chapter first summarizes key findings and contributions of this research and then discusses major limitations. Last, possible future directions of this research for further exploring the spatial patterns of income inequality and crime are suggested.

7.1 Key Findings

Each of the three manuscripts answered important individual research questions. In the first manuscript, the spatial patterns of within-area and across-area income inequality at the CT and DA scales were explored using ESDA tools. The following research question was addressed:

Which zones in the City of Toronto have significant income inequality problems?

The answer to this question is sensitive to spatial scale, since the DA scale captured greater variability and more detailed local variation in income inequality compared to the CT scale. Nevertheless, some noteworthy locations were identified at both spatial scales. First, for within-area income inequality, the central region of the city (from Old Toronto to North York) has higher levels of within-CT and within-DA income inequality. Second, for overall across-area income inequality, the central-western region of the city and western Scarborough have lower income levels compared to other zones. Third, for local across-area income inequality, some CTs and DAs have significantly lower income levels than their surrounding areas, most of which are near higher-income areas clustered in the centre of the city. Some CTs and DAs with significantly higher income levels than their surrounding areas are dispersed across the city. Last, many CTs and DAs in the core of Old Toronto require particular attention since they exhibit both higher within-area income inequality and overall lower income levels.

In the second manuscript, the relationship between income inequality and five major crime types (assault, robbery, auto theft, break and enter, and theft over $5,000) were investigated using different regression models at the CT and DA scales. The following research question was addressed:

Does income inequality increase major crime rates in the City of Toronto?

The answer to this question is sensitive to the crime type, statistical model, and spatial scale being considered. First, the use of spatial models improved model fit in both the frequentist and Bayesian frameworks. The Bayesian shared component model, which accounts for the interactions between crime types, further strengthened the model performance. Second, within-area income inequality, represented by the Gini coefficient, generally increases crime rates at both spatial scales. Third, among neighbouring CTs, two property crime types (break and enter and theft over $5,000) are more likely to occur in relatively rich CTs while two violent crime types (assault and robbery) are more likely to occur in relatively poor CTs. Last, among neighbouring DAs, all major crime types are more likely to occur in richer DAs compared to their poorer neighbours.

In the third manuscript, the spatiotemporal patterns of five major crime types (assault, robbery, auto theft, break and enter, and theft over $5,000) were analyzed using Bayesian modelling at the DA scale. The following research question was addressed:

How do the spatial patterns of major crimes change between business days and non-business days in Old Toronto?

First, in the entire Old Toronto area, non-business days tend to generate more incidents of violent crimes (assault and robbery) compared to business days, while the changes in property crimes (auto theft, break and enter, and theft over $5,000) are insignificant. Second, the local temporal patterns in DAs vary across space. Comparing non-business days to business days, DAs close to the southern shoreline have higher violent crime risks and DAs in the north tend to have lower property crime risks. Lower crime risks of theft over $5,000 and higher crime risks of auto theft on non-business days compared to business days were also found in the south. Third, schools are associated with higher violent crime risks on business days compared to non-business days, while BIAs and parks are associated with higher risks of break and enter and theft over $5,000, respectively, on non-business days compared to business days. Last, despite observed significant local temporal patterns, spatial hotspots of crime do not change significantly between business days and non-business days. Major spatial hot spot locations include the downtown areas, areas around Yonge Street and areas close to the shoreline or harbourfront. Unfavourable sociodemographic environments, as well as the presence of BIAs and parks, are positively associated with local crime risk.

7.2 Research Contributions

This thesis has theoretical, methodological and practical contributions to existing research on income inequality and crime. From a theoretical perspective, this thesis contributes to understanding the spatial patterns of income inequality and crime. The first and second manuscripts demonstrated the MAUP effects on income inequality and crime. Results showed that different spatial scales affect the quantification of income inequality and crime and alter the income inequality-crime relationship. Therefore, the spatial unit of analysis should be selected with caution.

The second and third manuscripts together examined some environmental criminology theories, including social disorganization theory, rational choice theory and opportunity theories, which attribute the spatiotemporal variation of crime to environmental conditions, such as income inequality and business areas. Theoretically, income inequality is positively associated with crime, meaning that crime rates tend to increase when income inequality increases. Results in the second manuscript showed that this theoretical relationship is true only for certain types of crime; for example, within-area income inequality at the CT scale increases break and enter but not auto theft. For the same type of crime, this relationship can also be sensitive to the spatial scale and the type of income inequality. For example, within-area income inequality increases auto theft at the DA scale but not at the CT scale; robbery at the CT scale is positively associated with across-area income inequality but not with within-area income inequality.

Opportunity theories for crime indicate that crime occurrences tend to cluster at locations and times with high levels of activities. The third manuscript assessed the spatiotemporal variation of crime between business days and non-business days based on these theories and identified the impacts of three categories of built environments (schools, parks, and business areas) that have variable activity patterns on different days of the week and year. For example, the presence of schools, which typically close on weekends and holidays, might lead to lower violent crime risks on non-business days compared to business days due to reduced activities.

From a methodological perspective, although this research did not develop new spatial data analysis techniques, it extended the use of existing methods to new applications and scenarios. The first manuscript showed that the use of ESDA tools can provide interesting insights into small-area spatial patterns of income inequality. It also presented an application of a novel multivariate LISA tool to multiple income statistics. Recognizing the advantages of Bayesian modelling in small-area crime analysis, the second and third manuscripts applied the Bayesian approach in spatial and spatiotemporal contexts, respectively. The flexibility of Bayesian modelling was demonstrated; for example, the second manuscript adopted a model that accounted for the interactions between crime types, which is difficult to achieve using frequentist approaches. The second manuscript also suggested that the choice of statistical models affects the results of the risk factor analysis for crime, since different results are attained from various frequentist and Bayesian models.

From a practical perspective, the findings of this research provide insights that are relevant for policy and planning decisions related to inequality reduction and crime prevention in the City of Toronto. First, maps presented in this thesis indicate locations of income inequality hot spots and crime hot spots, which highlight areas that require more attention in future policymaking. For example, several CTs and DAs with higher within-area income inequality, lower median incomes, and higher crime risks are located within downtown Toronto, which require strengthened crime control and inequality reduction measures. Second, maps in the third manuscript indicate the locations where crime risks differ between non-business days and business days, which provides useful information for developing policing strategies on weekends and holidays in the Old Toronto area. For example, on non-business days, more police officers may be assigned to the southern part of Old Toronto, where the risks of violent crime increase compared to business days. Third, findings from this research on the impacts of income inequality, built environment, and other sociodemographic conditions on crime can aid with the future prediction and modelling of crime in urban areas. Police departments should expect more crime occurrences in areas with characteristics that are evidently associated with crime and implement appropriate crime prevention; for example, more crime occurrences can be predicted around parks, especially for theft over $5,000 on non-business days, which can aid in planning police patrol and video surveillance measures.

7.3 Research Limitations

Although the limitations to each study were described within the individual manuscripts, some challenges encountered in the research as a whole are worth discussing. This section reviews major research limitations in two aspects. The first is related to data collection and variable preparation. The second concerns the spatiotemporal units and extents of analysis in this research.

7.3.1 The Issues of Data and Variable Selection

This research used three groups of variables based on secondary data, (a) sociodemographic variables based on the 2016 census data of Canada, (b) crime counts based on the police-reported crime data in Toronto, and (c) three built environment variables based on Toronto open data. More variables were considered in the research design process, especially in the second and third studies to quantify risk factors for crime (police activities, eating and drinking establishments, etc.), but no available datasets were found.

Variable selection was ultimately restricted by data availability and quality. The census was the only available data source to quantify socioeconomic and demographic conditions in small spatial units. Therefore, the selection of variables was constrained, and the Gini coefficient, an important indicator of income inequality used in this research, could only be approximated based on the available census income statistics. Moreover, the 2016 census used in this research may not accurately represent the sociodemographic conditions during the study period (2015-2019) of the second and third studies. In addition to sociodemographic conditions, the third study included characteristics of the built environment, which were all represented by binary variables because there was little information to quantify the sizes of the built environments or volumes of visitors present in the built environments.

In terms of the crime data, major issues of concern include the definitions of crime types, reporting rates and spatial information. Toronto police categorized major crimes into five types and excluded all sexual violations (Toronto Police Service, 2020b). Other data providers may have different definitions of crimes and hence the modelling results of the five major crime types in this research may not apply to other study areas. As for the crime reporting rates, it is well-known that police-reported crime data do not capture all crime incidents. According to Moreau (2019), reporting rates vary across crime types and the overall crime reporting rate in Canada was only 31% in 2014. As a result, this may significantly constrain the reliability of the crime modelling results in this research. The other issue related to crime data is the inaccuracy of spatial information and geocoding of cases or incidents. All recorded crime occurrences are offset to the nearest road intersections to protect privacy (Toronto Police Service, 2020b). This could lead to misplaced crime occurrences in area-based studies, especially in small-area analyses such as in this research.

7.3.2 The Issues of Spatiotemporal Units and Extents

Area-based spatial data analysis using artificial boundaries is subject to the MAUP. The MAUP has two aspects: the scale effect, which concerns the impacts of different spatial resolutions, and the zoning effect, which concerns the impacts of different boundaries at the same spatial resolution (Jelinski & Wu, 1996; Openshaw, 1984). Recognizing the MAUP, the first two manuscripts assessed the scale effects on income inequality and crime by comparing the results at the CT and DA scales. However, how the analysis results would change at other spatial scales (e.g., neighbourhood) remains unknown. The zoning effect was not explored in this research. The choices of spatial units were restricted to census geographic units since the census was used as a major data source. Furthermore, the MAUP effects on income inequality measures are complicated, and it is difficult to define the geographic contexts in which income inequality is perceived (see Section 2.5.5 and Section 4.6.2).

In addition to the MAUP, the temporal dimension added to crime modelling in the third study may lead to the modifiable temporal unit problem (MTUP). Similar to the MAUP, the MTUP also involves the scale effect and the zoning effect (Cheng & Adepeju, 2014). The scale effect in the context of the third manuscript implies possibly different crime patterns on different types of days within non-business days (e.g., weekends versus public holidays). The zoning effect applies to the definitions of weekends and holidays. According to Felson and Poulsen (2003), it is inappropriate for criminologists to use midnight as a way to separate and define different days of the week. However, in this research, weekends and holidays could only be defined based on calendar days because the crime data did not have high resolution temporal information available.

Another limitation pertains to both spatial and temporal extents of analysis. The spatial extents of this research are the City of Toronto (the first and second manuscripts) and Old Toronto (the third manuscript), while the temporal extent is 2015-2019 for crime modelling. The results of this research may not apply to other study regions and study periods. For example, the income inequality-crime relationship presented in the second manuscript may not remain true in other spatiotemporal extents because of possible differences in data collection methods, spatial unit definitions, and overall sociodemographic conditions among other conditions. Indeed, the positive association between within-DA income inequality and crime in Toronto City observed in the second study was not found in the third study in Old Toronto[2]. One possible cause of this discrepancy may be the consistently high levels of within-DA income inequality in Old Toronto (see the results in the first manuscript in Chapter 2), which resulted in within-DA income inequality not being identified as a significant risk factor of crime. Moreover, Old Toronto may be characterized by higher population mobility. This means that more crime incidents may not be related to local residents, but more related to transient populations. These hypotheses require further investigation.

[2] Note that the models developed in this research are different in the two studies. The model in the third manuscript used crime counts instead of crime rates and included more explanatory variables. To ensure the discrepancy was not caused by the models themselves, testing was conducted by applying the models in the second manuscript to the data of Old Toronto. The results showed no significantly positive association between within-DA income inequality and crime.

7.4 Future Directions

Each manuscript provides insights into future directions and further analyses that could be conducted to supplement the findings of this research. This section recommends future directions in a broader context for studying the links between income inequality and crime. First, alternative data collection methods, such as via residential surveys, can be used to capture neighbourhood socioeconomic variables such as income inequality. Since income inequality has detrimental psychological impacts on individuals, future research could potentially survey the subjective perceptions of income inequality, as well as its relationship to the perceived fear of crime. Moreover, the survey method could potentially address the uncertain geographic context problem (UGCoP), which recognizes the deviation of the areal unit in which the variables are measured from the true geographic context (Kwan, 2012). In the context of income inequality, individuals living in the same areas may perceive income inequality in different areas from different daily activities (e.g., going to work). Therefore, it may be meaningful to survey individual activity patterns along with perceptions of income inequality and analyze the spatial patterns of perceived income inequality accordingly. Moreover, there may be interesting relationships with the fear of crime to explore, since the psychological perception of crime and the actions individuals may take to prevent victimization may also be related to their socioeconomic profile, such as income and education.

Second, in addition to comparing the results at different spatiotemporal scales, some data-driven methods in Bayesian modelling may be used to address the manifestation of the MAUP and the MTUP in the analysis of relationships between income inequality and crime. For example, in health research, Jaya and Folmer (2020) applied agglomerative hierarchical clustering to the dependent variable based on the smallest spatiotemporal unit to produce different cluster configurations. Cluster-specific regression coefficients were added to the Bayesian spatiotemporal model and the optimal clustering scale was identified by comparing the performance of models using different cluster configurations.

Finally, modelling methods used in this research can be extended to analyze more dimensions of income inequality and crime. For income inequality, future research could potentially explore its spatiotemporal variation using income data of different years and to analyze how other sociodemographic factors (economic developments, education, ethnicity, etc.) may affect income inequality. For crime analysis, small-area spatiotemporal modelling of different types of crime can potentially be applied in more research contexts to validate criminology theories and how they can be used to improve crime prevention and control measures. For example, based on opportunity theories, there may be interesting spatiotemporal relationships to explore relating to links with extreme weather, the COVID-19 pandemic, and global warming, which may affect routine activities in urban built environments and the subsequent manifestation of crime.

Furthermore, while crime modelling in this research was mostly based on social factors, more characteristics of the physical environment could be considered in future crime modelling research. This could address larger built environments (landscape and land use) and smaller physical facilities (e.g., light posts and security cameras). It may also be interesting to assess the spatiotemporal heterogeneity of crime in areas with similar social conditions based on the micro-level effects of physical factors, such as the impacts of the installation of streetlights or security cameras within their coverage areas. Such research could further reveal and compare the roles of social and physical environments in the spatiotemporal distribution of crime and aid future planning for designing built environments that effectively prevent crime.

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Appendix A: Regression Variables (Chapter 4)

Table A1. Descriptive statistics for the explanatory variables

Variable	Mean	Minimum	Maximum	Standard deviation
Census tracts				
Gini coefficient	38.74	25.85	64.13	5.74
% richer than the poorest neighbour	44.67	-57.01	281.48	48.22
% Movers	39.27	18.20	88.18	11.97
Ethnic fractionalization	60.00	0.00	86.41	17.62
% no post-secondary degrees	31.41	7.25	69.23	14.05
Population density	7.87	0.10	82.43	8.05
Dissemination areas				
Gini coefficient	36.57	10.00	75.73	7.02
% richer than the poorest neighbour	64.26	-72.27	632.24	79.60
% Movers	36.16	0.00	97.86	14.32
Ethnic fractionalization	54.76	0.00	88.41	19.58
% no post-secondary degrees	31.51	0.00	85.29	15.59
Population density	9.35	0.05	482.27	13.99

Table A2. Descriptive statistics for log-transformed crime rates

Crime type	Mean	Minimum	Maximum	Standard deviation
Census tracts				
Assault	-3.74	-8.94	-0.31	0.98
Robbery	-5.37	-8.94	-1.89	0.97
Auto theft	-5.21	-8.94	-2.11	0.84
Break and enter	-4.52	-8.94	-0.98	0.83
Theft over $5,000	-6.44	-8.94	-2.57	0.85
Dissemination areas				
Assault	-4.04	-8.94	0.13	1.24
Robbery	-5.34	-8.94	-1.03	1.03
Auto theft	-5.10	-8.94	-0.88	0.93
Break and enter	-4.56	-8.94	-0.98	1.00
Theft over $5,000	-5.90	-8.94	-2.12	0.73

Note: To avoid zeros in the transformation, crime rate = (1+crime count) / population.

Table A3. Pearson correlation matrices for log-transformed crime rates

	Assault	**Robbery**	**Auto theft**	**Break and enter**
Census tracts				
Robbery	0.81 *			
Auto theft	0.54 *	0.56 *		
Break and enter	0.62 *	0.57 *	0.60 *	
Theft over $5,000	0.55 *	0.53 *	0.52 *	0.68 *
Dissemination areas				
Robbery	0.71 *			
Auto theft	0.50 *	0.51 *		
Break and enter	0.61 *	0.55 *	0.57 *	
Theft over $5,000	0.48 *	0.50 *	0.53 *	0.60 *

Note: Positive values indicate positive associations. * indicates $p < 0.0001$ (very significant).

Appendix B: Frequentist Regression Results (Chapter 4)

Note: * indicates $p < 0.05$. In each spatial regression, either the spatial lag model or the spatial error model was used based on the LM statistics.

Table B1. OLS regression results at the CT scale

	Assault	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Intercept	-6.716*	-7.232*	-5.719*	-6.395*	-8.288*
Gini coefficient	0.029*	0.019*	0.009	0.043*	0.023*
% richer than the poorest neighbour	0.002*	0.001	0.002*	0.004*	0.003*
% Movers	0.019*	0.013*	0.001	0.008*	0.026*
Ethnic fractionalization	0.012*	0.004	0.001	0.000	0.001
% No post-secondary degrees	0.016*	0.017*	0.009*	-0.001	0.000
Population density	-0.025*	-0.021*	-0.042*	-0.029*	-0.031*

Table B2. Frequentist spatial regression results at the CT scale

	Assault	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Model	Spatial lag	Spatial lag	Spatial error	Spatial lag	Spatial lag
$\boldsymbol{\rho}$	0.371*	0.373*		0.397*	0.197*
$\boldsymbol{\lambda}$			0.475*		
Intercept	-4.495*	-4.544*	-5.204*	-4.142*	-6.734*
Gini coefficient	0.022*	0.012	0.004	0.033*	0.019*
% richer than the poorest neighbour	0.001	0.000	0.001	0.003*	0.002*
% Movers	0.015*	0.012*	-0.001	0.006	0.023*
Ethnic fractionalization	0.009*	0.002	0.003	0.001	0.001
% No post-secondary degrees	0.010*	0.011*	0.000	-0.001	-0.001
Population density	-0.028*	-0.026*	-0.047*	-0.031*	-0.031*

Table B3. OLS regression results at the DA scale

	Assault	Robbery	Auto theft	Break and enter	Theft over $5,000
Intercept	-6.210*	-6.664*	-5.119*	-5.299*	-6.279*
Gini coefficient	0.022*	0.018*	0.004	0.025*	0.013*
% richer than the poorest neighbour	0.002*	0.001*	0.001*	0.002*	0.001*
% Movers	0.012*	0.004*	-0.005*	0.001	0.002*
Ethnic fractionalization	0.009*	0.004*	-0.001	-0.001	-0.002*
% No post-secondary degrees	0.015*	0.012*	0.006*	-0.003*	0.000
Population density	-0.018*	-0.014*	-0.019*	-0.019*	-0.012*

Table B4. Frequentist spatial regression results at the DA scale

	Assault	Robbery	Auto theft	Break and enter	Theft over $5,000
Model	Spatial lag	Spatial error	Spatial error	Spatial error	Spatial error
ρ	0.274*				
λ		0.302*	0.372*	0.326*	0.264*
Intercept	-4.684*	-6.372*	-5.082*	-5.059*	-6.102*
Gini coefficient	0.019*	0.015*	0.005*	0.021*	0.011*
% richer than the poorest neighbour	0.001*	0.001*	0.001*	0.002*	0.001*
% Movers	0.010*	0.001	-0.005*	-0.001	0.001
Ethnic fractionalization	0.008*	0.003*	-0.001	-0.001	-0.002*
% No post-secondary degrees	0.011*	0.010*	0.004*	-0.004*	-0.001
Population density	-0.019*	-0.016*	-0.018*	-0.020*	-0.013*

Appendix C: WinBUGS Code for the Spatial Shared-Component Model (Chapter 4)

```
model {
	for (i in 1 : N) {                        # loop through areas
	for (k in 1 : 5) {                        # five crime types
		y[k,i]  ~ dpois(pmu[k,i])           # crime count modelled in Poisson distribution
		##### parameterization of log(crime rate)#####
		log(pmu[k,i]) <- log(p[i])+log.mu[k,i]
		log.mu[k,i] ~ dnorm(m[k,i], prec.U[k])            # spatial random effects
		m[k,i] <- alpha[k]                                # intercept
		 + beta[k,1] * (X_gin[i] - mean(X_gin[]))         # Gini
		 + beta[k,2] * (X_prp[i] - mean(X_prp[]))     #%Richer than the poorest Neighbour
		 + beta[k,3] * (X_mov[i] - mean(X_mov[]))         # % movers
		 + beta[k,4] * (X_eth[i] - mean(X_eth[]))         # ethnic fractionalization
		 + beta[k,5] * (X_nps[i] - mean(X_nps[]))         # no post-secondary degrees %
		 + beta[k,6] * (X_ppd[i] - mean(X_ppd[]))         # population density
		 + phi[i]*l[k]                                    # shared spatial component
		 + S[k,i]                                         # type-specific spatial effects
		U[k,i] <- log.mu[k,i] - m[k,i]                    # recover the spatial random effects
	}
	}

	#####priors#####
	## ICAR prior on spatially structured effects; fixed variance for the shared component ##
	for (k in 1 : 5) { S[k,1:N] ~ car.normal(adj[], weights[], num[], prec.S[k]) }
	phi[1:N] ~ car.normal(adj[], weights[], num[], 1)
	##half-normal distributions for the factor loadings##
	for (k in 1:5){ l[k] ~ dnorm(0, 0.001)I(0, )  }
	##un-informative distributions for the intercept and the regression coefficients##
	for (k in 1 : 5) { alpha[k] ~ dflat() }
	for (k in 1 : 5) { for (j in 1:6) {beta[k,j] ~ dnorm(0,0.001)} }
	##Gamma distributions for the variance terms##
	for (k in 1 : 5) {
		prec.S[k] ~ dgamma(0.5,0.0005)
		prec.U[k] ~ dgamma(0.5,0.0005)
	}

}
```

Appendix D: Bayesian Regression Results (Chapter 4)

Table D1. Results of the Bayesian non-spatial model at the CT scale

	Assault	Robbery	Auto theft	Break and enter	Theft over $5,000
Intercept	-3.734 (-3.805, -3.663)	-5.410 (-5.489, -5.332)	-5.237 (-5.298, -5.176)	-4.521 (-4.578, -4.465)	-6.600 (-6.677, -6.524)
Gini coefficient	0.029 (0.014, 0.044)	0.022 (0.005, 0.038)	0.007 (-0.006, 0.020)	0.043 (0.031, 0.055)	0.027 (0.011, 0.042)
% richer than the poorest neighbour	0.002 (0.000, 0.004)	0.001 (-0.001, 0.003)	0.002 (0.000, 0.003)	0.004 (0.002, 0.005)	0.003 (0.001, 0.005)
% Movers	0.021 (0.012, 0.029)	0.015 (0.006, 0.024)	0.003 (-0.004, 0.010)	0.010 (0.003, 0.016)	0.031 (0.022, 0.039)
Ethnic fractionalization	0.012 (0.006, 0.017)	0.003 (-0.002, 0.009)	0.001 (-0.004, 0.005)	-0.001 (-0.005, 0.003)	0.001 (-0.004, 0.007)
% No post-secondary degrees	0.017 (0.010, 0.025)	0.020 (0.012, 0.028)	0.011 (0.005, 0.017)	0.001 (-0.005, 0.006)	0.002 (-0.006, 0.010)
Population density	-0.024 (-0.035, -0.013)	-0.021 (-0.033, -0.009)	-0.044 (-0.053, -0.034)	-0.027 (-0.036, -0.019)	-0.035 (-0.046, -0.024)

Table D2. Results of the Bayesian spatial type-specific model at the CT scale

	Assault	Robbery	Auto theft	Break and enter	Theft over $5,000
Intercept	-3.733 (-3.807, -3.66)	-5.411 (-5.497, -5.326)	-5.239 (-5.303, -5.175)	-4.524 (-4.586, -4.461)	-6.597 (-6.678, -6.518)
Gini coefficient	0.005 (-0.011, 0.021)	0.001 (-0.018, 0.019)	-0.002 (-0.016, 0.011)	0.021 (0.008, 0.034)	0.011 (-0.007, 0.028)
% richer than the poorest neighbour	-0.001 (-0.003, 0.001)	-0.002 (-0.004, 0.000)	0.001 (-0.000, 0.002)	0.001 (-0.000, 0.003)	0.002 (-0.000, 0.003)
% Movers	0.008 (-0.001, 0.017)	0.008 (-0.002, 0.017)	0.000 (-0.007, 0.007)	0.001 (-0.006, 0.008)	0.021 (0.012, 0.031)
Ethnic fractionalization	0.017 (0.010, 0.023)	0.006 (-0.001, 0.014)	0.005 (-0.001, 0.010)	0.002 (-0.003, 0.008)	0.006 (-0.000, 0.013)
% No post-secondary degrees	0.006 (-0.003, 0.016)	0.005 (-0.006, 0.016)	-0.003 (-0.011, 0.006)	-0.004 (-0.012, 0.004)	-0.005 (-0.015, 0.004)
Population density	-0.043 (-0.056, -0.031)	-0.042 (-0.056, -0.028)	-0.052 (-0.062, -0.041)	-0.045 (-0.055, -0.035)	-0.047 (-0.060, -0.034)

Table D3. Results of the Bayesian spatial shared component model at the CT scale

	Assault	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Intercept	-3.729 (-3.764, -3.693)	-5.409 (-5.549, -5.344)	-5.241 (-5.323, -5.18)	-4.528 (-4.586, -4.478)	-6.576 (-6.631, -6.522)
Factor loadings (*l*)	1.649 (1.517,1.791)	1.835 (1.671,2.000)	1.340 (1.216,1.469)	1.321 (1.209,1.453)	1.626 (1.450,1.813)
Gini coefficient	-0.003 (-0.017, 0.010)	-0.007 (-0.023, 0.008)	-0.009 (-0.021, 0.003)	0.015 (0.004, 0.026)	0.000 (-0.015, 0.015)
% richer than the poorest neighbour	-0.002 (-0.003, -0.001)	-0.003 (-0.004, -0.001)	0.000 (-0.001, 0.001)	0.001 (-0.001, 0.002)	0.000 (-0.001, 0.002)
% Movers	0.008 (0.001, 0.015)	0.005 (-0.003, 0.013)	0.001 (-0.006, 0.007)	0.000 (-0.006, 0.006)	0.020 (0.012, 0.028)
Ethnic fractionalization	0.014 (0.008, 0.019)	0.004 (-0.002, 0.010)	0.003 (-0.002, 0.008)	0.000 (-0.004, 0.005)	0.003 (-0.002, 0.009)
% No post-secondary degrees	0.003 (-0.005, 0.012)	0.001 (-0.009, 0.011)	-0.007 (-0.014, 0.001)	-0.006 (-0.013, 0.001)	-0.011 (-0.019, -0.002)
Population density	-0.055 (-0.065, -0.045)	-0.055 (-0.068, -0.043)	-0.062 (-0.072, -0.053)	-0.052 (-0.060, -0.043)	-0.061 (-0.073, -0.050)

Table D4. Results of the Bayesian non-spatial model at the DA scale

	Assault	Robbery	Auto theft	Break and enter	Theft over $5,000
Intercept	-4.173 (-4.215, -4.13)	-5.998 (-6.059, -5.939)	-5.437 (-5.476, -5.398)	-4.739 (-4.775, -4.704)	-7.031 (-7.099, -6.965)
Gini coefficient	0.026 (0.019, 0.032)	0.029 (0.021, 0.038)	0.003 (-0.003, 0.009)	0.029 (0.024, 0.035)	0.030 (0.022, 0.038)
% richer than the poorest neighbour	0.002 (0.001, 0.002)	0.002 (0.001, 0.003)	0.001 (0.001, 0.002)	0.002 (0.002, 0.002)	0.002 (0.001, 0.003)
% Movers	0.018 (0.014, 0.021)	0.016 (0.012, 0.021)	0.003 (-0.000, 0.006)	0.008 (0.005, 0.011)	0.023 (0.019, 0.028)
Ethnic fractionalization	0.012 (0.010, 0.015)	0.010 (0.007, 0.014)	0.001 (-0.001, 0.003)	0.000 (-0.002, 0.002)	0.002 (-0.001, 0.006)
% No post-secondary degrees	0.017 (0.014, 0.020)	0.020 (0.016, 0.024)	0.009 (0.006, 0.011)	-0.004 (-0.007, -0.002)	-0.001 (-0.005, 0.003)
Population density	-0.027 (-0.031, -0.022)	-0.028 (-0.034, -0.022)	-0.042 (-0.046, -0.037)	-0.032 (-0.036, -0.029)	-0.034 (-0.040, -0.028)

Table D5. Results of the Bayesian spatial type-specific model at the DA scale

	Assault	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Intercept	-4.171 (-4.213, -4.128)	-5.992 (-6.055, -5.930)	-5.442 (-5.482, -5.403)	-4.739 (-4.776, -4.702)	-7.017 (-7.086, -6.949)
Gini coefficient	0.013 (0.006, 0.019)	0.019 (0.010, 0.028)	0.002 (-0.003, 0.008)	0.014 (0.008, 0.019)	0.015 (0.006, 0.024)
% richer than the poorest neighbour	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)	0.002 (0.001, 0.002)
% Movers	0.010 (0.007, 0.014)	0.010 (0.005, 0.015)	0.001 (-0.002, 0.004)	0.001 (-0.002, 0.004)	0.015 (0.011, 0.020)
Ethnic fractionalization	0.015 (0.011, 0.018)	0.012 (0.008, 0.016)	0.003 (0.000, 0.006)	0.003 (0.000, 0.005)	0.005 (0.001, 0.009)
% No post-secondary degrees	0.012 (0.008, 0.016)	0.012 (0.007, 0.018)	0.001 (-0.002, 0.005)	-0.001 (-0.005, 0.002)	0.000 (-0.005, 0.006)
Population density	-0.038 (-0.043, -0.033)	-0.041 (-0.048, -0.035)	-0.045 (-0.050, -0.041)	-0.044 (-0.048, -0.040)	-0.047 (-0.054, -0.041)

Table D6. Results of the Bayesian spatial shared component model at the DA scale

	Assault	**Robbery**	**Auto theft**	**Break and enter**	**Theft over $5,000**
Intercept	-4.174 (-4.199, -4.149)	-5.973 (-6.022, -5.926)	-5.468 (-5.503, -5.433)	-4.767 (-4.798, -4.736)	-7.025 (-7.090, - 6.960)
Factor loadings (*l*)	2.545 (2.455, 2.635)	2.844 (2.713, 2.968)	1.802 (1.710, 1.896)	1.945 (1.866, 2.031)	2.357 (2.229, 2.494)
Gini coefficient	0.007 (-0.000, 0.014)	0.013 (0.004, 0.022)	0.000 (-0.007, 0.006)	0.010 (0.004, 0.016)	0.010 (0.001, 0.019)
% richer than the poorest neighbour	0.001 (0.000, 0.002)	0.001 (0.000, 0.002)	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)
% Movers	0.008 (0.004, 0.011)	0.006 (0.002, 0.011)	-0.001 (-0.004, 0.003)	0.000 (-0.003, 0.003)	0.011 (0.007, 0.016)
Ethnic fractionalization	0.01 (0.007, 0.014)	0.005 (0.001, 0.01)	0.000 (-0.003, 0.003)	0.000 (-0.003, 0.003)	0.000 (-0.004, 0.005)
% No post-secondary degrees	0.011 (0.006, 0.016)	0.009 (0.003, 0.015)	0.000 (-0.004, 0.004)	-0.001 (-0.005, 0.003)	-0.002 (-0.008, 0.004)
Population density	-0.052 (-0.058, -0.047)	-0.059 (-0.066, -0.052)	-0.056 (-0.061, -0.051)	-0.054 (-0.059, -0.05)	-0.063 (-0.07, -0.056)

Appendix E: WinBUGS Code for the Spatiotemporal Model with Explanatory Variables (Chapter 6)

```
model{
	for(i in 1:N){						# loop through areas
		for(j in 1:T){					# loop through time periods
			y[i,j] ~ dpois(nmu[i,j])	# crime count modelled in Poisson distribution
			##### parameterization of log(daily crime risk)#####
			log(nmu[i,j]) <- log.mu[i,j]+ log(n[j])
			log.mu[i,j] <- alpha + (S[i] + U[i] + S.Cov[i]) + b0*t[j] + (b[i]+T.Cov[i])*t[j]
		}
		##### Explanatory variables#####
		S.Cov[i] <- beta[1] * (X_GIN[i]-mean(X_GIN[]))   #Spatial explanatory variables
			+ beta[2] * (X_PRP[i]-mean(X_PRP[]))
			+ beta[3] * (X_LIR[i]-mean(X_LIR[]))
			+ beta[4] * (X_MOV[i]-mean(X_MOV[]))
			+ beta[5] * (X_ETH[i]-mean(X_ETH[]))
			+ beta[6] * (X_NPS[i]-mean(X_NPS[]))
			+ beta[7] * (X_POP[i]-mean(X_POP[]))
			+ beta[8] * (X_PPD[i]-mean(X_PPD[]))
			+ beta[9] * (X_BIA[i]-mean(X_BIA[]))
			+ beta[10]* (X_SCH[i]-mean(X_SCH[]))
			+ beta[11] * (X_GSP[i]-mean(X_GSP[]))

		T.Cov[i] <- beta[12] * (X_BIA[i]-mean(X_BIA[])) #Temporal explanatory variables
			+ beta[13]* (X_SCH[i]-mean(X_SCH[]))
			+ beta[14] * (X_GSP[i]-mean(X_GSP[]))

		##### Prior for the unstructured spatial effects#####
		U[i] ~ dnorm(0,prec.U)
	}

	#####Priors#####
	alpha ~ dflat()
	S[1:N] ~ car.normal(adj.sp[], weights.sp[], num.sp[], prec.S)
	b0 ~ dnorm(0,0.001)
	b[1:N] ~ car.normal(adj.sp[], weights.sp[], num.sp[], prec.b)
	prec.S ~ dgamma(0.5,0.0005)
	prec.b ~ dgamma(0.5,0.0005)
	prec.U ~ dgamma(0.5,0.0005)
	for(k in 1:14){beta[k] ~ dnorm(0,0.001)}
}
```