

Spatiotemporal crime patterns and the urban environment:  
Evidence for planning and place-based policy

by

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## **Author's Declaration**

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

## Statement of Contributions

Contributions to the three research articles included in this dissertation are described below. As the first author for all articles, Matthew Quick initiated and conceptualized the studies, conducted the literature reviews, performed data analyses, prepared the figures, and drafted and revised the articles.

Article 1 (Chapter 2): *Spatiotemporal modelling of correlated small-area outcomes: Analyzing the shared and type-specific patterns of crime and disorder*

This article was co-authored with Dr. Guangquan Li and Dr. Jane Law. Dr. Li and Dr. Law both provided feedback on data analysis and model interpretation. This paper has been published at *Geographical Analysis*. This article is a stand-alone contribution, however it does extend previous work done by Matthew Quick, Dr. Li, and Dr. Ian Brunton-Smith (see Quick et al., 2018a).

Article 2 (Chapter 3): *Time-varying relationships between land use and crime: A spatiotemporal analysis of small-area seasonal property crime trends*

This article was co-authored with Dr. Jane Law and Dr. Guangquan Li. Dr. Law helped to construct the initial model and to select the variables for analysis. Dr. Li helped with the specification and interpretation of the time-varying regression coefficients. This paper has been published at *Environment and Planning B: Urban Analytics and City Science*.

Article 3 (Chapter 4): *Multiscale spatiotemporal patterns of crime: A Bayesian cross-classified multilevel modelling approach*

This article was sole-authored by Matthew Quick. This paper is currently under review at *Journal of Geographical Systems*.

## **Abstract**

Crime and disorder influence individual quality of life, community social cohesion, and processes of neighbourhood and urban change. Existing studies that analyze local crime and disorder patterns generally focus only on where crime and disorder events occur. However, understanding the spatiotemporal patterning of crime and disorder, or both where and when events occur, is central to the design, implementation, and evaluation of crime prevention policies and programs. This dissertation explores the connections between local spatiotemporal patterns of crime and disorder, the urban environment, and urban planning through three research articles. Each article makes theoretical contributions that improve understanding of how characteristics of the urban environment influence crime and disorder, methodological contributions that advance spatiotemporal modeling of small-area crime data, and policy-oriented contributions that inform place-based crime prevention initiatives in urban planning, local government, and law enforcement.

The first research article examines if, and how, physical disorder, social disorder, property crime, and violent crime share a common spatial pattern and/or a common time trend. Three multivariate models are compared and the results of the best-fitting model show that all crime and disorder types share a common spatial pattern and a common time trend. The shared spatial pattern is found to explain the largest proportion of variability for all types of crime and disorder, and type-specific spatiotemporal hotspots of crime and disorder are identified and investigated to contextualize broken windows theory. This study supports collective efficacy theory, which contends that multiple crime and disorder types are associated with same underlying processes, and highlights specific areas where crime prevention interventions should be designed to address all, or only one, type(s) of crime and disorder.

The second article quantifies the time-varying relationships between land use and property crime for twelve seasons at the small-area scale. A set of spatiotemporal regression models with time-constant and time-varying regression coefficients are compared and the results of the best-fitting model show that parks and eating and drinking establishments exhibit recurring seasonal relationships, where parks are more positively associated with property crime during spring/summer and eating and drinking establishments are more positively associated with property crime during autumn/winter. Local land use composition is shown to have a more substantial impact on the spatial, rather than the spatiotemporal, patterning of crime. Applied to policy, the results of this article inform the design and coordination of time-constant and time-varying crime prevention initiatives as implemented by urban planning and law enforcement agencies, respectively.

The third article investigates the spatiotemporal patterning of violent crime across multiple spatial scales. Violent crime data are measured at the small-area scale (lower-level units) and small-areas are nested in neighbourhoods, electoral wards, and patrol zones (higher-level units). A cross-classified multilevel model is applied to accommodate the three higher-level units that are non-hierarchical and have overlapping boundaries. Accounting for sociodemographic, built environment, and civic engagement characteristics, planning neighborhoods, electoral wards, and patrol zones are found to explain approximately fourteen percent of the total spatiotemporal variation of violent crime. Planning neighborhoods are the most important source of variation amongst the higher-level units. This article advances understanding of the multiscale processes that influence where and when violent crime events occur and provides area-specific crime risk information within the geographical frameworks used by policymakers in urban planning (neighbourhoods), local government (wards), and law enforcement (patrol zones).

Broadly, this dissertation advances research focused on the connections between crime and disorder and the urban environment by (1) quantifying the degree to which spatiotemporal crime and disorder patterns are stable and/or dynamic, (2) examining the relationships between crime and disorder and local sociodemographic and built environment characteristics, (3) illustrating a set of statistical models that make sense of spatiotemporal crime and disorder patterns at the small-area scale, and (4) providing local spatiotemporal information that can be used to design and implement place-based crime prevention initiatives in urban planning, local government, and law enforcement.

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# Chapter 1: Introduction

## 1.1. Context

Crime and disorder influence individual quality of life, community social cohesion, and processes of neighbourhood and urban change. Crime victimization directly leads to physical injuries and psychological trauma and is indirectly associated with a variety of deleterious health outcomes and behaviours including anxiety, depression, fear of crime, and reduced participation in physical and social activities (Robinson and Keithley, 2000; Hirschfield, 2004; Chaix et al., 2006; Lorenc et al., 2012). Within communities, high levels of crime have been found to be associated with low social capital, poor cognitive performance, and elevated rates of all-cause mortality, heart disease, and low birth weight, and, at the city-scale, crime patterns influence the structural characteristics of neighbourhoods and the social-spatial processes of urban flight, suburbanization, neighbourhood decline, and gentrification (Warner and Rountree, 1997; Wilkinson et al., 1998; Forrest and Kearns, 2001; Lynch and Rasmussen, 2001; Sundquist et al., 2006; Sharkey, 2010; Lorenc, et al., 2012; Katzman, 1980; Skogan, 1990; Cullen and Levitt, 1999; Hipp, 2010; Kirk and Laub, 2010). In addition to these physical, emotional, psychological, and structural effects, the annual financial costs of crime in Canada have been estimated to be more than \$85 billion, as attributed to the direct and indirect impacts of crime victimization (\$61 billion), policing (\$11 billion), and the criminal justice system (\$9 billion) (Easton et al., 2014).

Motivated by the non-uniform spatial and temporal patterning of crime causes, crime events, and crime consequences, over a century of research has explored the relationships between crime and the urban environment. Historically, geographic crime research can be traced back to Guerry (1832) and Quetelet (1847), who observed spatial and temporal variations in crime across administrative regions in France and Belgium and linked these variations to the unequal distribution of wealth

(Friendly, 2007; Weisburd et al., 2009). Shifting focus to the neighbourhood scale, sociological research has highlighted the associations between community social dynamics and individual and group-level behaviours and outcomes and, in particular, has shown that areas with high crime rates are often characterized by high levels of residential mobility, population heterogeneity, and physical deterioration (Shaw and McKay, 1942; Abbott, 1997; Sampson et al., 2002). Most recently, research has investigated the situational characteristics of crime offenses and the ways in which potential offenders and crime targets converge at specific locations (Cohen and Felson, 1979; Sherman et al., 1989). Facilitated by innovations in data collection, processing, mapping, and computing (Manning, 1992; Chan, 2001), these studies have drawn attention to the non-ubiquitous spatiotemporal patterning of crime opportunities and to the clustering of crime events around specific features of the built environment (Weisburd et al., 2012; Bannister et al., 2017).

Alongside these theoretical developments have been methodological developments for analyzing spatial and spatiotemporal data. While the earliest studies relied on visual map comparisons between crime and census variables to identify high crime areas and to infer the associated data-generating processes (e.g., Guerry (1829) and Shaw and McKay (1942)), contemporary research, as driven by the availability of georeferenced crime datasets and the ubiquity of Geographic Information Systems in research and policy domains, has employed a variety of quantitative methods to characterize spatial crime patterns and to estimate the relationships between crime and the urban environment (Anselin, 2000; Levine, 2006). Of particular interest for theoretical innovation, policy development, and policy evaluation are approaches that simultaneously analyze spatial and temporal variations of crime, provide insight into the stable and/or dynamic nature of local crime patterns, and quantify if, and how, sociodemographic and/or built environment contexts influence these spatiotemporal patterns (Johnson, 2008; Groff et al., 2010; Weisburd et al., 2012; Law et al., 2014; Chun, 2014; Li et al., 2014).



Urban planning has traditionally been peripheral to both theory and analysis relating to the local spatial and spatiotemporal patterning of crime, however planning scholarship and planning practice are well-positioned to inform the application, interpretation, and policy translation of this research. While researchers and policymakers have long highlighted the connections between the urban environment and crime (e.g., Shaw and McKay (1942)), perhaps the first direct link between crime and urban planning was articulated by Jane Jacobs (1961, p.34), who noted that “eyes on the street” regulate human behaviour and deter potential offenders from engaging in criminal or disorderly acts. Within the planning profession, Newman (1972) formalized many of Jacobs’ observations through the concept of defensible space, which recommends that buildings, streets, and neighbourhoods be designed to promote territoriality, natural surveillance, and the clear demarcation of public and private spaces. Since these foundational works, interdisciplinary research in sociology, geography, urban planning, and statistics has continued to investigate and articulate the important role of urban planning – as an agency focused on land use policy and as a community-oriented institution that brings together residents around common goals – in shaping the social, economic, and political conditions that influence crime; in structuring land use, activity patterns, and the distribution of crime opportunities; and in implementing place-based crime prevention policies and programs (Brantingham and Brantingham, 1998; Kubrin and Weitzer, 2003; Sampson, 2012; Cozens, 2011).

## **1.2. Dissertation structure**

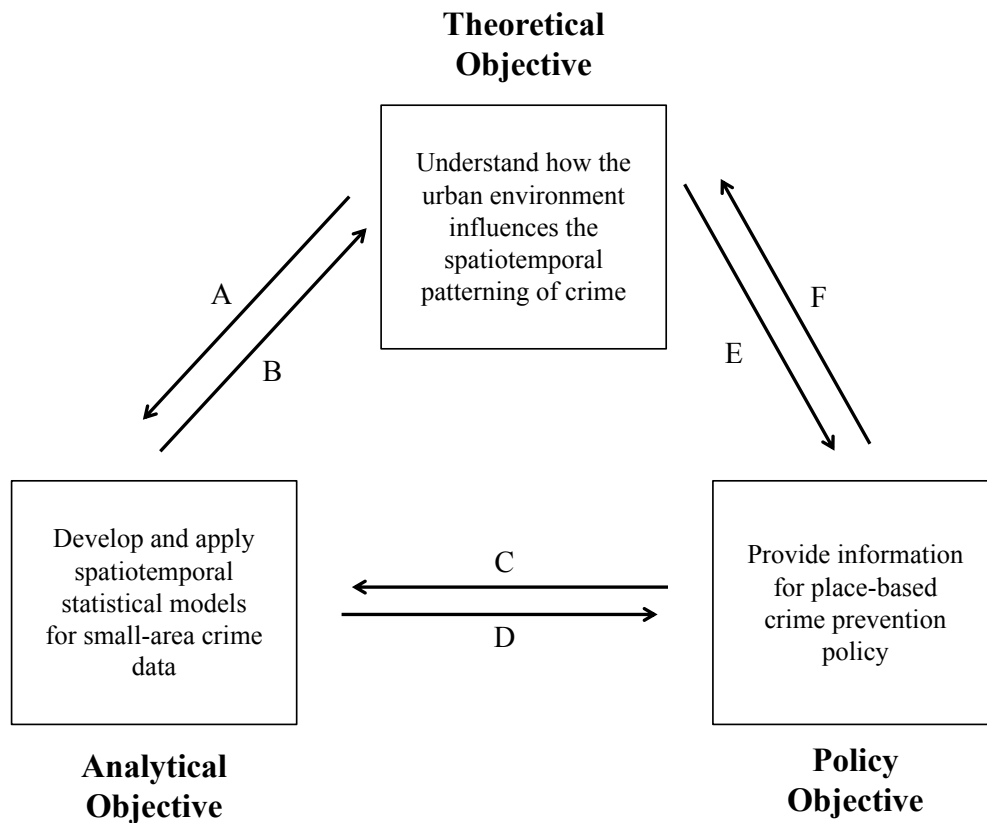
This dissertation explores the connections between crime and disorder, the urban environment, and urban planning in the Region of Waterloo, Ontario, Canada. This dissertation is composed of five chapters. In the following sections of this introductory chapter (Chapter 1), the theoretical, analytical, and policy-oriented objectives of this dissertation are outlined, the theories used to explain intra-urban crime patterns are reviewed, and the data used for this dissertation are detailed and examined.

Following the manuscript-based dissertation format outlined by the University of Waterloo School of

Planning, the next three chapters each feature one research article prepared for a peer-reviewed journal: Chapter 2 presents the first research article, titled *Spatiotemporal modelling of correlated small-area outcomes: Analyzing the shared and type-specific patterns of crime and disorder*; Chapter 3 presents the second research article, titled *Time-varying relationships between land use and crime: A spatiotemporal analysis of small-area seasonal property crime trends*; and Chapter 4 presents the third research article, titled *Multiscale spatiotemporal patterns of crime: A Bayesian cross-classified multilevel modelling approach*. In Chapter 5, the key findings and contributions of this dissertation are summarized, limitations are highlighted, and a number of areas for future study are recommended.

### **1.3. Dissertation objective and motivations**

There are three overarching objectives of this dissertation. The first objective is theoretical and aims to advance understanding of how local spatiotemporal crime patterns are influenced by the urban environment. The second objective is analytical and looks to develop, apply, and disseminate spatiotemporal statistical models that strengthen inference of complex small-area crime and urban environment data. The third objective is policy-oriented and endeavours to provide quantitative information for place-based crime prevention policies and programs designed and implemented by urban planning, local government, and law enforcement. These objectives are outlined in Figure 1.1 and discussed below.



- A: Theoretical hypotheses inform the design of spatiotemporal statistical models.
- B: The results of statistical models support (or refute) ecological crime theories.
- C: Existing policy frameworks inform data handling and the design of statistical models.
- D: The results of spatiotemporal analyses provide evidence for place-based policies.
- E: Ecological crime theories help to understand the processes to be addressed via policy.
- F: Policy evaluation contextualizes theoretical hypotheses and data-generating processes.

**Figure 1.1. The theoretical, analytical and policy objectives of this dissertation.**

### 1.3.1. Theoretical objectives

Theories developed to explain and interpret the relationships between crime and the urban environment primarily focus on the spatiotemporal patterning of crime, however most past studies have focused on the cross-sectional or spatial patterning of crime. Research that tests theoretical hypotheses using data from one time period cannot identify if spatiotemporal crime patterns are stable

(i.e., the local data-generating processes are relatively constant over time) or if spatiotemporal crime patterns are dynamic (i.e., the local data-generating processes change over time). Yet, understanding if, and why, crime patterns are stable or dynamic is required for theoretical validation and theoretical innovation. For example, while existing research has shown that community-level social dynamics and structural characteristics influence the spatial patterning of crime, little is known about how processes of neighbourhood change lead to crime increases or decreases (cf. Kirk and Laub, 2010; Papachristos et al., 2011; Barton and Gruner, 2015). Likewise, despite opportunity theories positing that behavioural activity patterns and corresponding features of the built environment influence both where and when crime events occur, few studies consider if the locations of crime clusters change over time or how the relationships between crime and the urban environment vary by hour, day, week, month, season, or year (cf. Weisburd et al., 2012; Andresen and Malleson, 2013; Felson and Boivin, 2015).

This dissertation asks and answers a number of questions that advance spatiotemporal theories used to explain the relationships between crime and the urban environment. Across all three research articles, I ask to what degree the data-generating processes associated with crime and/or disorder events were spatial (i.e., stable over time), temporal (i.e., stable over space), or spatiotemporal (i.e., vary over both space and time). Data-generating processes refer to the mechanisms hypothesized by ecological crime theories and are inferred through observed covariates, such as small-area structural characteristics and built environment features, as well as latent covariates, such as random effects terms that capture the spatial and/or temporal patterns of crime that are unaccounted for by the observed covariates. In general, I find that the observed and latent processes associated with crime and disorder patterns were relatively stable over time for five years (between 2011 and 2015; see Chapter 2 and Chapter 4) and for twelve seasons (between 2011 and 2014; see Chapter 3), which suggests that the processes leading to non-uniform spatiotemporal crime and disorder patterns were largely similar across multiple time periods.

Building off of this overarching theoretical objective, each research article in this dissertation asks and answers a more specific question that advances ecological crime theory. These theoretical contributions inform the design of spatiotemporal statistical models and the recommended attributes of crime prevention policy (Arrow A and Arrow E in Figure 1.1). In Chapter 2, I ask if, and to what degree, the spatiotemporal patterning of multiple crime and disorder types are explained by a common underlying spatial pattern, a common temporal pattern, and divergent type-specific spatial, temporal, and spatiotemporal patterns. This work challenges existing research that, despite using the same theories and risk factors, assumes that each crime type has a unique spatial pattern and is explained by unique data-generating processes (e.g., Weisburd et al. (1993) and Haberman (2017)). In Chapter 3, I ask how local land use composition influences the spatiotemporal patterning of property crime and I quantify the time-varying relationships between crime and a number of land use types. By identifying specific features of the built environment that influence dynamic crime patterns, this work builds on existing research that observes seasonal crime patterns but does not explain the underlying data generating-processes (e.g., Brunsdon et al. (2009) and Andresen and Malleson (2013)). In Chapter 4, I ask if the spatiotemporal patterning of violent crime is stable or dynamic across multiple spatial scales. This study accounts for a number of ecological crime theories at their hypothesized spatial scale and extends past work that focuses on only one theory and/or only one spatial scale.

### **1.3.2. Analytical objectives**

Past studies that examine how local crime patterns are influenced by the urban environment generally use cross-sectional methods that characterize the spatial patterning of crime for one time period but overlook how these patterns change over time. Broadly, methods used to analyze point-based and area-based spatiotemporal crime data can be classified as testing-based approaches, which quantify if one (sub)set of data is significantly different than a second (sub)set (e.g., cluster identification methods), or model-based approaches, which model the data-generating processes associated with

crime and disorder as a function of observed and/or unobserved covariates (e.g., regression models) (Robertson et al., 2010). Existing spatiotemporal crime studies have predominately used testing-based approaches to classify crime trends or identify crime clusters, such as group-based trajectory methods or the spatial scan statistic (Weisburd et al., 2012; Ceccato, 2005; Leitner and Helbich, 2011). These approaches, however, cannot not assess the degree to which crime patterns for the study region, or for specific small-areas, are stable or dynamic. Also, testing-based methods often do not provide area-specific risk estimates for all areas within a study region despite this information being central for theoretical exploration, policy development, and policy evaluation (see Section 2.3).

This dissertation develops, applies, and disseminates a set of statistical models that make sense of the complex relationships between spatiotemporal crime patterns and the urban environment. Specifically, this dissertation employs a set of Bayesian hierarchical models that partition small-area spatiotemporal crime and/or disorder counts into a set of observed covariates and one or more sets of spatial random effects, temporal random effects, and space-time random effects (see Chapters 2, 3, and 4) (Knorr-Held and Besag, 1988; Knorr-Held 2000). Summarizing the variability explained by each set of random effects terms quantifies the degree to which crime patterns vary over space, over time, or over space-time, and provides insights regarding the stable or dynamic nature of local crime patterns. In all three of the research articles, population size, variables capturing local structural characteristics, and a variable measuring the central business district were included in analysis to account for local risk factors commonly found to be associated with crime and disorder (Shaw and McKay, 1942; Sampson and Groves, 1989; Doran and Lees, 2005; Nelson et al., 2001).

This general modeling framework was modified within each research article to address specific theoretical hypotheses and policy objectives (Arrow B and Arrow D in Figure 1.1). In Chapter 2, I include multiple dependent variables and directly model the shared spatial pattern and the shared spatial time trend common to physical disorder, social disorder, property crime, and violent crime. This advances past work that explores the similarities and differences between multiple crimes by

comparing and contrasting the results of separate cluster identification techniques or separate regression models applied to a single crime type (see Section 2.3). In Chapter 3, I include time-varying regression coefficients to model the seasonal relationships between property crime and land use. This extends past work that visually compares seasonal spatial crime patterns but does not quantify how the relationships between crime and the built environment change over time (see Section 3.3). In Chapter 4, I add three higher-level units in a cross-classified multilevel model to allow for the small-area spatiotemporal violent crime patterns to be explained by data-generating processes across multiple spatial scales that have overlapping geographical boundaries. This work addresses the methodological limitations in past studies that analyze multilevel data that does not have overlapping boundaries or that compare the results of separate analyses conducted at different scales (e.g., Steenbeek and Weisburd (2016) and Ouimet (2000)).

### **1.3.3. Policy objectives**

Understanding and modeling the spatiotemporal relationships between crime and/or disorder and the urban environment provides information for the design, implementation, and evaluation of place-based crime prevention policy. For example, the information obtained from the spatiotemporal statistical models applied in this dissertation can be used to identify priority locations for place-based crime prevention policies and programs; assess the timing or scheduling of these policies and programs; characterize the types of spatial, temporal, or spatiotemporal characteristics and/or processes that should be accounted for; and highlight the types of agencies, or the types of collaborations between agencies, that may be most effective at addressing a specific community safety issue. Cross-sectional research, in contrast, helps to identify locations for crime prevention interventions but does not consider the timing of these initiatives or the different spatial, temporal, and spatiotemporal processes that lead to crime. Illustrating this point, Johnson et al. (2008) review the policy implications of identifying spatiotemporal crime hotspots and propose that areas with

stable and high levels of crime be addressed through built environment changes or other modifications to the social and physical environment, that areas with highly fluctuating levels of crime be addressed by temporary police patrols or other deployable resources, and that areas with cyclic crime trends be targeted for recurring and scheduled interventions.

This dissertation provides information for place-based crime prevention policies and programs in urban planning, local government, and law enforcement. In all three research articles, areas characterized by large population sizes, high levels of residential instability, and high levels of socioeconomic disadvantage, as well as areas that are located in the central business districts, were, on average, more likely to have high crime and disorder than areas with small populations, with low mobility and high income, and that were located outside of the city centres. Also, spatial crime patterns were found to be relatively stable over time. Combined, this evidence suggests that crime prevention interventions should focus primarily on the spatially stable processes and risk factors. Urban planners, in particular, can address stable neighbourhood features through land use plans and zoning by-laws that define suitable residential and non-residential land uses, and through urban design guidelines that emphasize crime prevention through natural surveillance.

The policy contributions of each research article also inform theories focused on the relationships between crime patterns and the built environment as well as the design of spatiotemporal analytical models (Arrows C and F in Figure 1.1). In Chapter 2, I identify areas where crime prevention policy should be designed for multiple crime and disorder types or just one crime/disorder type, and I contextualize broken windows-inspired urban policies by showing that the transitions between disorder and crime, as anticipated by broken windows theory, were relatively infrequent in the study region. In Chapter 3, by distinguishing the land use types that exhibit time-constant and time-varying relationships with crime, I outline how urban planners and law enforcement can work hand-in-hand to reduce property crime through time-constant land use policy and time-varying policing initiatives, respectively. In Chapter 4, I show that planning neighbourhoods



are relatively more important than electoral wards and police patrol zones for explaining the spatiotemporal variation of violent crime and suggest that urban planners possess the geographical perspective and the policy tools necessary to address the crime across multiple spatial scales.

#### **1.4. Theoretical perspectives on crime and the urban environment**

Broadly, two research paradigms have been used to interpret and explain the local intra-urban patterning of crime. Neighbourhood effects theories, specifically social disorganization theory and collective efficacy theory, focus on the relationships between neighbourhood structural characteristics, resident-based social dynamics, and criminal behaviour. Opportunity theories, specifically routine activity theory and crime pattern theory, focus on the interactions between behavioural activity patterns, features of the urban environment, and the spatiotemporal patterning of crime offenses. Together, these research paradigms help to conceptualize where and when crime events occur and provide a theoretical framework for operationalizing the urban environment through social, economic, demographic, political, and built environment characteristics (Smith et al., 2000; Braga and Clarke, 2014).

##### **1.4.1. Neighbourhood effects theories**

Social disorganization theory hypothesizes that neighbourhood structural characteristics influence informal social control and that, in some neighbourhoods, low informal social control leads to high levels of crime (Bursik Jr., 1988; Warner and Rountree, 1997; Kubrin and Weitzer, 2003). Arising from, and exercised through, the social ties between residents, informal social control is defined as the capacity of a group to regulate behaviour in order to realize common values (Silver and Miller, 2004; Warner, 2007; Sampson and Groves, 1989; Bellair and Browning, 2010). Social disorganization theory was first proposed by Shaw and McKay (1942) to explain the spatial distribution of juvenile delinquents in Chicago neighbourhoods but has since been found to help

understand the spatial patterning of both violent and non-violent crime offenses at a variety of spatial scales, in residential and non-residential areas, and in both rural and urban contexts (Kawachi et al., 1999; Ouimet, 2000; Osgood and Chambers, 2000; Barnett and Mencken, 2002; Kubrin and Weitzer, 2003; Taylor et al., 2005; Jacob, 2006; Wong, 2012).

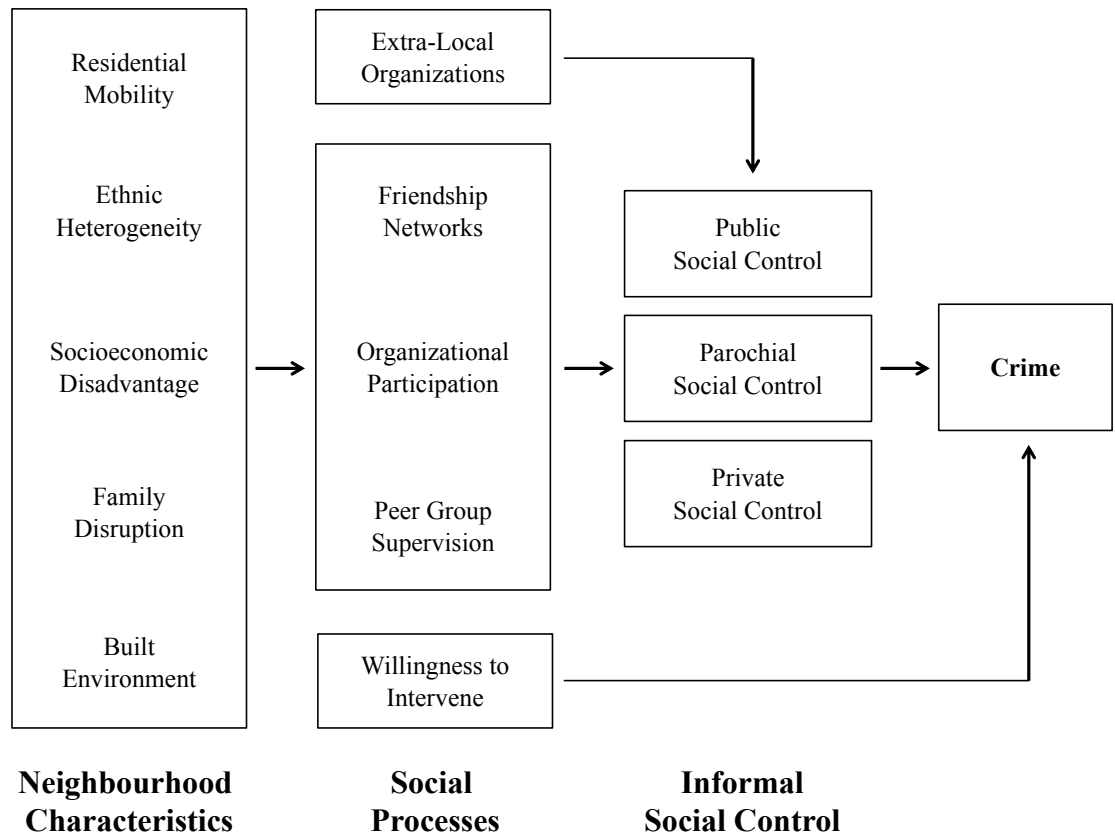
Focusing on the ways in which informal social control is established and enforced within and between communities, the systemic model of social disorganization contends that there are three types of informal social control: private social control, parochial social control, and public social control. Private social control manifests from the intimate relationships amongst friends and family; parochial social control is exercised through the non-intimate relationships amongst members of local organizations, such as schools, churches, and neighbourhood associations; and public social control results from the social relationships between communities and extra-local organizations, such as law enforcement and local government (Hunter, 1985; Bursik Jr. and Grasmick, 1993). Specific examples of private social control include social support, criticism, or ostracism of criminal or disorderly behaviour; examples of parochial social control include supervision of neighbourhood residents, informal surveillance of neighbourhood activities, and intervention in suspicious activities; and examples of public social control include community-based actions that work to secure political and economic resources from extra-local organizations to improve community safety and address issues of collective concern (Bursik Jr. and Grasmick, 1993; Warner, 2007; Velez, 2001).

Operationalizing social disorganization theory, neighbourhood-scale informal social control is often inferred via residential mobility, ethnic heterogeneity, and socioeconomic disadvantage, as high levels of these characteristics are thought to impede the formation of social ties amongst residents (Shaw and McKay, 1942). Sampson and Groves (1989), in particular, highlight three mechanisms – local friendship networks, peer group supervision, and organizational participation – that link neighbourhood structural characteristics to informal social control. For private social control between friends and family, high residential mobility and high ethnic heterogeneity challenge the development

of local friendship networks because residents are unfamiliar with each other and may have differing interpretations of what constitutes appropriate behaviour. For parochial social control between community members, high socioeconomic disadvantage, high ethnic heterogeneity, and high residential mobility are thought to weaken local institutions and reduce organizational participation, and limit supervision over peer groups because residents are less likely to intervene in the actions of unfamiliar residents (Bursik Jr. and Grasmick, 1993; Warner and Rountree, 1997; Bursik Jr., 1999; Veysey and Messner, 1999). For public social control, disadvantaged neighbourhoods are hypothesized to have fewer ties to public officials compared to neighbourhoods with high-income and influential community members, and are therefore less likely to obtain the resources necessary to address issues related to the public good, such as improving community safety (Velez, 2001).

Recent interpretations of social disorganization theory also include family disruption, urbanization, and features of the built environment as characteristics that influence local informal social control. Family disruption, often measured through the percent of single parent families, is thought to decrease peer group supervision, disperse local friendship networks, and lead to weak private and parochial social ties (Wong, 2012). Similarly, urbanization is hypothesized to be associated with lower participation in formal organizations and limited supervision of peer groups (Bursik, Jr., 1999; Veysey and Messner, 1999; Jacob, 2006). Focusing on the built environment, Taylor et al. (1995) propose that business-centred non-residential land uses, including mixed land uses, undermine the formation of common values among residents, attract large numbers of non-residents, and limit social interaction amongst neighbourhood residents (Taylor et al., 1995; Sampson and Raudenbush, 1999; Stucky and Ottensmann, 2009). Alternatively, resident-centred non-residential land uses such as schools, playgrounds, and parks have been found to be associated with low crime as they facilitate social interaction among residents (Wilcox et al., 2004; Cohen et al., 2008).

Recognizing the limitations of social disorganization theory in explaining criminal behaviour in contemporary urban and suburban neighbourhoods, Sampson et al. (1997) proposed collective efficacy theory. Formally, collective efficacy is defined as “social cohesion among neighbors combined with their willingness to intervene on behalf of the common good (Sampson et al., 1997: 918).” Unlike social disorganization theory, collective efficacy theory recognizes that communities with weak social ties developed through frequent and cursory social interactions may also have community members that will take action to establish and maintain community safety (Forrest and Kearns, 2001; Sampson and Wikstrom, 2008; Bellair and Browning, 2010; Groff, 2014). One example is suburban neighbourhoods, which have weak social ties because residents prioritize privacy, but also have high informal social control because residents share common values and take action to regulate local behaviours (Morenoff et al., 2001). Willingness to intervene on behalf of the common good, the task-specific dimension of collective efficacy, has been measured through resident perceptions that neighbours will intervene if children are observed skipping school or disrespecting adults, and the degree to which residents would mobilize to ensure that local fire service or local community centres remain operational if threatened with budget cuts (Sampson et al., 1997; Bruinsma et al., 2013). A conceptual model of the data-generating mechanisms hypothesized by social disorganization theory and collective efficacy theory are shown in Figure 1.2.



**Figure 1.2. Conceptual model of social disorganization theory and collective efficacy theory.**

### **1.4.2. Opportunity theories**

Opportunity theories of crime assume that offenders are rational actors and that crime offenses result from a decision-making process that is influenced by situational factors pertaining to where and when a crime opportunity arises (Eck and Weisburd, 1995; Cornish and Clarke, 2008). Routine activity theory hypothesizes that crime offenses occur when motivated offenders, suitable targets, and a lack of capable guardianship converge in space and time (Cohen and Felson, 1979). Historically, routine activity theory was first proposed to explain increasing rates of property crime victimization between 1950 and 1975 as a function of society-level changes to daily activity patterns from inside to outside of the home (less capable guardianship) and increased production and consumption of material goods (more attractive targets) (Felson, 2008; Miethe et al., 1987; Kennedy and Forde, 1990). For example,

early routine activity theory research found that victimization was more common amongst young adults, unmarried adults, and individuals who participated in night-time activities as these lifestyle characteristics were associated with more frequent participation in activities outside of the home (Miethe et al., 1987; Kennedy and Forde, 1990).

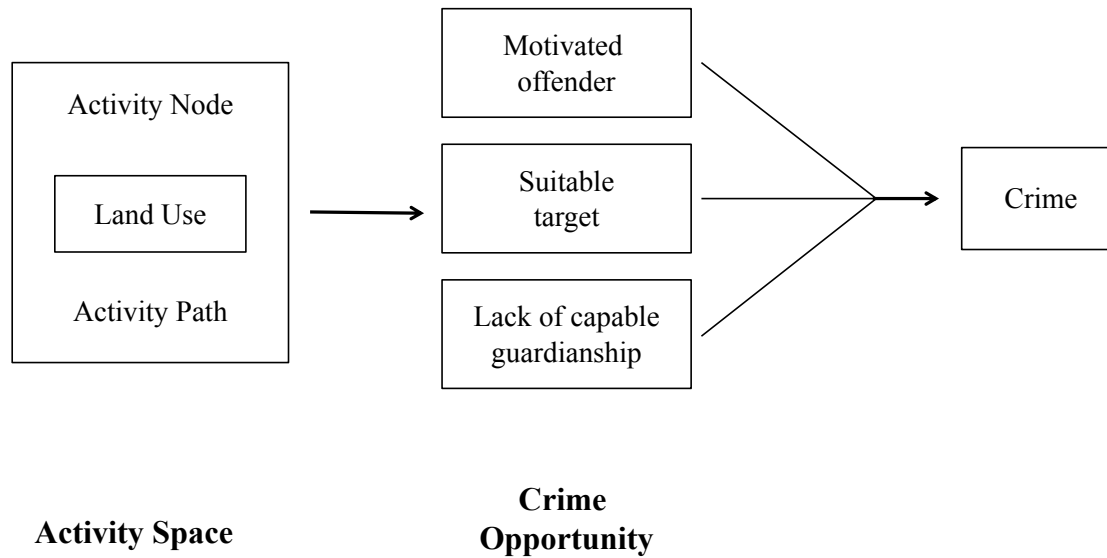
Geographically situating routine activity theory, Sherman et al. (1989) explored the clustering of reported crime offenses at the address-scale and found that fewer than five percent of addresses had more than fifty percent of all reported crimes, and that high crime addresses were often located at or near specific land uses, including bars, parks, liquor stores, malls, and hotels. From this, it was concluded that crime opportunities often cluster at specific places in the urban environment and that these locations are where crime opportunities and crime offenses – as indicated by the convergence of motivated offenders, suitable targets, and a lack of capable guardianship – are most frequent. Notably, Sherman et al. (1989) was foundational to the development of opportunity theories in geographic crime research and to the field of study called Criminology of Place, which examines the concentration of crime at specific addresses, intersections, and streets (Weisburd et al., 2012; Bannister et al., 2017).

Crime pattern theory traces the movements of people through the urban environment and argues that the spatiotemporal patterning of crime events is closely associated with the activity spaces of potential offenders. Activity spaces are the collection of activity nodes and activity paths that one travels through during their routine activities (Brantingham and Brantingham, 1993). Specifically, activity nodes are locations where large populations come together for daily activities (e.g., employment areas, schools, or shopping areas) and activity paths are the travel routes between activity nodes (e.g., transit stations, roads). Crime pattern theory proposes that, as offenders move through the urban environment, they become aware of crime opportunities and engage in criminal behaviour when there are both suitable targets available and a lack of capable guardianship present (Brantingham and Brantingham, 2008; Eck and Weisburd, 1995). Crime pattern theory also

recognizes that activity spaces are embedded within the environmental backcloth, or the social, political, and physical contexts in which activity spaces are located (Groff et al., 2010; Deryol et al., 2016).

Crime pattern theory highlights three types of activity nodes; crime generators, crime attractors, and crime detractors. Crime generators are locations that are easily accessible to the public, are included in many activity spaces, and are the locations of opportunistic crime offenses; crime attractors are locations where offenses are driven by explicit criminal motivations; and crime detractors are locations not often included in activity spaces (Weisburd et al., 2012; Groff and Lockwood, 2014). For example, crime generating land uses for property crimes include bars, schools, highways, and parks (Matthews et al., 2010) and crime generating land uses for violent crimes include high density residential areas and commercial land uses (Stucky and Ottensmann, 2009). It is also possible that land uses are both crime generators and attractors, as Kinney et al. (2008) note that commercial land uses are crime generators and crime attractors for both motor vehicle thefts and assaults.

Activity paths are also considered as a crime generating feature of the physical environment (Braga and Clarke, 2014). For example, streets with high connectivity, as measured by the number of turns onto a street, high traffic volume, and many public transportation stops are included in many activity spaces and are locations where opportunistic offending may occur (Greenberg and Rohe, 1984; Beavon et al., 1994; Groff et al., 2014; Bernasco and Block, 2011; Groff and Lockwood, 2014). In general, past studies have consistently shown that areas with high traffic activity nodes and/or high traffic activity paths have relatively higher levels of crime than areas without, or with low traffic, activity nodes and/or activity paths (Wilcox and Eck, 2011). A conceptual model of the data-generating mechanisms hypothesized by routine activity theory and crime pattern theory are shown in Figure 1.3.



**Figure 1.3. Conceptual model of routine activity theory and crime pattern theory.**

### **1.4.3. Spatial structure**

As described above, neighbourhood effects and opportunity theories describe the processes contributing to crime within areas. However, intra-urban crime patterns have been shown to be spatially correlated such that the level of crime at nearby locations is relatively more similar than the level of crime at distant locations (Anselin, 2000; Townsley, 2009). Past research has suggested that the spatial correlation of crime results from processes related to crime diffusion, whereby crime in one area increases the likelihood of crime in adjacent areas (Cohen and Tita, 1999; Baller et al., 2005), or processes related to the spillover effects of area-specific characteristics, whereby the effects of sociodemographic or built environment characteristics located in one area also influence crime in adjacent areas (Bernasco and Block, 2011; Zhu et al., 2004). From an analytical perspective, spatial correlation of crime is attributable to missing explanatory variables and/or mismatches between the spatial units used to measure crime and the spatial units through which the theories and the data-generating processes operate. In this study, spatial structure of crime is modeled via one or more sets of random effects parameters within each Bayesian hierarchical model. In Chapters 2 and 3, spatially



structured random effects terms are included to capture residual spatial correlation between adjacent areas, and in Chapter 4, higher-level random effects terms (in a multilevel model) capture residual clustering of crime between the small-areas that are nested in a higher-level unit. Random effects terms are interpreted as unobserved covariates and, therefore, the treatment of spatial structure in this dissertation makes no assumptions regarding the presence of spillover or diffusion processes.

## **1.5. Crime patterns and urban planning**

Despite often being adjacent to the development and application of spatial and spatiotemporal crime theories, urban planning scholarship and urban planning practice are well-positioned to inform, develop, and translate neighbourhood effects theories and opportunity theories to policy. The connections between planning and both neighbourhood effects theories and opportunity theories are described below.

### **1.5.1. Planning and neighbourhood effects**

Through observing city- and neighbourhood-level changes in population composition, social-spatial inequality, and processes of urban change, planning research helps to inform the application and interpretation of neighbourhood effects theories. Focusing on population composition, social disorganization research has often operationalized ethnic heterogeneity as the percent of immigrants within a small-area under the assumption that there is a positive relationship between immigrant concentration and crime (e.g., Ouimet (2000) and Andresen (2006a)). Planning and urban geography research, however, has shown that Canadian cities often receive skilled or economic immigrants with high socioeconomic status, and that many immigrant families have strong relationships with community members (parochial social control) as well as high rates of participation in local organizations (public social control) (Ley and Smith, 2000; Martinez Jr. et al., 2010; Kubrin, 2013). These observations suggest that indicators of immigrant concentration may not be suitable for

measuring ethnic heterogeneity and that alternative operationalizations, such as variables that measure the relative mixing of ethnic groups or languages spoken within a geographic area, may be more appropriate for inferring informal social control in the Canadian context (Kubrin and Wo, 2016). Indeed, recent studies have found that regions, cities, and neighbourhoods with higher proportions of immigrants often have lower crime rates (MacDonald et al., 2013; Ousey and Kubrin, 2018).

Focusing on social-spatial inequality and processes of urban change, planning research has shown that North American cities are experiencing rising levels of income inequality, increasing levels of segregation amongst high- and low-income neighbourhoods, and a growing concentration of disadvantaged neighbourhoods in the inner suburbs (i.e., away from the city centre) (Ross et al., 2004; Walks and Bourne, 2006; Ades et al., 2012; Fong and Shibuya, 2000; Smith and Ley, 2008). This is important because it challenges the interpretation of variables capturing urbanization and residential mobility in social disorganization and collective efficacy theories. For example, planning research indicates that many Canadian city centres are increasingly composed of high-income neighbourhoods that may exhibit the structural characteristics of a socially organized community (i.e., low socioeconomic disadvantage and low ethnic heterogeneity) (Hulchanski, 2010). At the same time, many inner cities have experienced considerable social, economic, and built form changes as a result of gentrification, or the process of neighbourhood re-investment that leads to the displacement of low socioeconomic status residents by middle or high socioeconomic status residents, and corresponding private investments in housing (Ley, 1992; Walks and Maaranen, 2008). Linking these planning observations with neighbourhood effects theories provides one explanation as to why many Canadian cities have experienced decreasing levels of crime since the “urban revival” began in the early 2000s (Allen, 2018; Florida, 2017) and underscores the importance of considering national, regional, municipal, and neighbourhood-level contexts when analyzing and explaining local spatiotemporal crime patterns.

Translating neighbourhood effects research into policy, urban planning can be conceptualized as a policy agency responsible for land use and/or an institution responsible for working with residents to address local issues. As a policy agency, planning provides the framework for locating and defining both residential and non-residential land uses. These features directly influence residential mobility, as areas with high densities of rental housing typically have higher levels of residential mobility than neighbourhoods composed of single-detached and owner-occupied dwellings (Lockwood, 2007). For example, the siting of public housing, which is typically characterized by high residential mobility, is often cited as a planning decision that influences neighbourhood informal social control and local levels of crime (Sampson, 2011). Note that past studies evaluating the effects of building, modifying, or demolishing public housing on crime are inconclusive (Kondo et al., 2018). Likewise, the siting and design of new suburban communities, which also have high levels of residential mobility, are a set of planning decisions that have been shown to be negatively associated with violent crime (Sparks, 2011).

While planning policy can, and does, influence the social processes that generate non-uniform spatial and spatiotemporal crime patterns, crime also influences the contexts in which planners operate. For example, crime and fear of crime shape where people choose to live, how people travel, and the success of urban development, infrastructure, and revitalization projects (Jacobs, 1961; Kohm, 2009; Greenberg and Rohe, 1984; Ranasinghe 2011). As such, low crime and low fear of crime are two factors that enable planning projects to realize their intended objectives around improving public space, economic development, and building vibrant and inclusive neighbourhoods. Crime also influences processes of community change, as high levels of crime and/or disorder have been shown to increase residential mobility, increase the prevalence of minority and disadvantaged households, and decrease housing prices as individuals and families self-select out of high crime areas (Skogan, 1990; Lynch and Rasmussen, 2001; Hipp, 2009; Bogges and Hipp, 2010; Hipp, 2011; Morenoff and Sampson, 1997). These bi-directional processes, where neighbourhood characteristics

shape the mechanisms leading to crime, which, in turn, shape neighbourhood structure, accelerate and entrench social-spatial inequalities within the urban environment and set the contexts for how planners should approach policy design, implementation, and evaluation (Walks and Bourne, 2006; Garnett, 2010).

As an institution responsible for working with residents, urban planning provides opportunities for community members to participate and reach consensus on issues of local importance, such as development projects (e.g., zoning by-laws) and community plans. This aligns with the task-specific dimension of collective efficacy (i.e., the degree to which residents intervene on behalf of the common good) and parallels past operationalizations of collective efficacy that focus on how residents will take action in response to change in local service and amenity provision (Sampson et al., 1997; Bruinsma et al., 2013). Indeed, past research suggests that participatory planning processes that work towards collective goals, such as family- and pedestrian-friendly planning, and the development or expansion of resident-centred services and land uses, such as libraries, public transit, and parks, improve collective efficacy and reduce crime (Rukus and Warner, 2013). When thought of as an institution that brings together community members to discuss, debate, and resolve local issues, planning practice is also linked to public social control; interacting with practicing planners during consultation processes strengthens the relationships between community members and government and provides an opportunity for communities to secure resources from extra-local organizations (Velez, 2001; Sampson, 2011; see Chapter 4).

### **1.5.2. Planning and opportunity theories**

Despite the tensions between many planning objectives and the intuitive policy implications of routine activity theory and crime pattern theory (i.e., reduce or eliminate crime generating land uses that are essential to city functioning), planning practice has integrated the principles of opportunity theories in a variety of ways. The most apparent connection between opportunity theories and

planning practice is crime prevention through environmental design (CPTED). Historically, CPTED can be traced back to Jacobs's (1961, p.34) observations that well-used streets are safe streets and that 'eyes on the street,' or natural surveillance by residents and pedestrians, regulate human behaviour and deter potential offenders from engaging in criminal or disorderly behaviour. Providing a framework for planning and urban design, Newman (1972) proposed defensible space, which recommends that buildings, streets, and neighbourhoods be designed to promote territoriality, increase natural surveillance, and clearly demarcate public and private spaces (Loukaitou-Sideris, 1999). At the building scale, defensible space recommends windows and doors look onto streets, ample public realm lighting, and landscapes designed to distinguish property lines. At the neighbourhood scale, defensible space argues that communities should be approximately three to six blocks in size and that through-traffic be limited in order to increase social interaction and facilitate a sense of territoriality or ownership among residents (Beavon et al., 1994; Newman, 1997). In contemporary planning, architecture, and urban design, operationalizations of "CPTED" largely captures the principles outlined by defensible space theory (Greenberg and Rohe, 1984).

Like opportunity theories of crime, CPTED assumes that offenders are rational, that situational factors influence the decision-making process, and that the presence and/or perception of capable guardianship influences the likelihood that a crime opportunity will result in a crime offense (Wortley and Mazerolle, 2008). CPTED, therefore, attempts to prevent criminal behaviour through modifying the built environment to increase guardianship and perceptions of guardianship (Cozens, 2008). In practice, this has been accomplished by ensuring that there is ample lighting near building entrances, in parking lots, and along walkways, and designing buildings and landscapes to promote visibility of the pedestrian environment (Plaster et al., 2003; American Planning Association, 2013). CPTED also recommends that planners work to decrease the attractiveness of targets and clearly delineate public and private spaces by erecting physical barriers such as fences and gates (Clarke, 1995; Cozens, 2008). Importantly, while physical design may increase the perceptions of capable guardianship, the

degree to which residents will intervene as guardians or place managers is closely tied to the relationships amongst local residents that are, in turn, shaped by neighbourhood structural characteristics and social dynamics (Merry, 1981; Greenberg and Rohe, 1984).

Connecting crime pattern theory and the activity space concept to planning practice, Beavon et al. (1994: 138) note that “modern city planning practices... create the opportunity network for crime.” However, the intuitive policy implications of crime pattern research – restricting or strategically locating crime generating land uses – may not be an appropriate or tractable policy solution given the competing priorities of urban planning around economic development, livability, and public service provision. Many crime generating land uses, such as bars, restaurants, transit stations, and shopping malls, serve essential functions in the urban environment and, the priorities of urban planning, such as downtown redevelopment, often go hand-in-hand with increasing densities of these crime generating land uses (Gruenewald et al., 1996). Perhaps a more amenable solution to incorporating the concept of crime generating land uses into policy, then, is to treat them as a starting point to explain where and when crime events occur, and then to explore other approaches to crime prevention and reduction. For example, the concept of crime generating land uses may help explain why crime offenses cluster in downtown areas and can be used to inform local CPTED guidelines, local housing policies, or local police patrols (Wikstrom, 1995; Plaster et al., 2013).

In addition to building and community design, recent studies have provided insights into how other types of built environment modifications can increase perceptions of guardianship and reduce crime and disorder (Mair and Mair, 2003; Spader et al., 2016; Sadler et al., 2017; Kondo, 2018). Grounded in broken windows theory, which hypothesizes that disorder reduces perceptions of guardianship and leads to increases in crime (see Chapter 2), Branas et al. (2011) used a difference-in-difference analysis to evaluate the effect of a lot greening program, which transforms vacant lots into park-like settings, on a set of health and community safety outcomes in Philadelphia. The results of this study indicated that greening vacant lots was associated with reductions in gun assaults and

vandalism. Similarly, Branas et al. (2018) randomly assigned vacant lots into treatment (greening) or control (no greening) groups and found that lot greening led to reduced perceptions of crime and vandalism, fewer gun-related violent crimes and burglaries, and improved perceptions of safety. From these studies, it is clear that planning-led crime prevention initiatives focused on built environment changes can, and do, influence the mechanisms that influence crime as hypothesized by routine activity and crime pattern theories.

## **1.6. Data measuring crime, disorder, and the urban environment**

This dissertation uses three types of data: police call-for-service data that measures crime and disorder, census data that measures small-area population characteristics, and built environment data that characterizes local land use composition.

### **1.6.1. Quantitative crime and disorder data**

All quantitative crime data reflect a combination of real crime events, institutional definitions of crime, the techniques used to capture and record crime, and the processes and methods used to manage, handle, and disseminate crime data (Biderman and Reiss Jr., 1967). Three types of crime data are commonly used in spatial and spatiotemporal analyses at the city scale or smaller: official crime data, victimization data, and call-for-service data (Easton et al., 2014). Briefly, official crime data measure criminal acts charged under criminal law and are generally distributed by national-level statistical or criminal justice agencies; victimization data measure characteristics of criminal activity as recalled by victims and are typically collected via surveys; and call-for-service data measure crime incidents reported to police and are collected and distributed by municipal or regional police agencies (Klinger and Bridges, 1997). Each type of crime data have strengths and weaknesses regarding the potential biases in data collection and the spatiotemporal information associated with crime events, as discussed below.

### **1.6.2. Call-for-service data**

Call-for-service data are commonly used to measure crime and disorder at the small-area scale (Sherman et al., 1989; Warner and Pierce, 1993; Klinger and Bridges, 1997; Kurtz et al., 1998; Andresen, 2006a; Braga and Bond, 2008; Brunson et al., 2009; Yang, 2010). The prevalence of call-for-service data in geographic crime research is related to the growth of geographically-focused technologies in policing, such as computer aided dispatch systems that automatically record all incidents reported to police; a growing interest in crime mapping, place-based crime prevention policies, and hotspot policing; and data transparency and open data initiatives that make call-for-service datasets available to researchers and the public (Sherman et al., 1989; Brantingham and Brantingham, 1990; Burisk Jr. and Grasmick, 1993; Weisburd and Lum, 2005).

Call-for-service data includes all events that are reported to the police regardless of seriousness and each reported incident typically includes both spatial and temporal information. Regarding potential biases in data collection, call-for-service data is less likely to be influenced by police practices and/or victim recall issues that are common to official crime data and victimization data, respectively (Klinger and Bridges, 1997). For example, the main source of official crime data in Canada is the Uniform Crime Reporting Survey, which counts the number of crimes that have led to a criminal charge under the Criminal Code of Canada as well as the number of criminal incidents in which police are confident a crime was committed, the number of chargeable incidents, the number of adults charged, and the number of charged and not charged youth (Statistics Canada, 2016). Because many crimes are not reported to police, do not result in a charged offense, or are removed because they are not the most serious offense recorded during one event, official crime data may undercount events perceived as minor by the police or by victims (Sherman et al., 1989; Statistics Canada, 2016). Similarly, victimization survey data may be influenced by memory problems and/or response biases such that participants are more likely to recall serious crimes, as perceived by the victim, and less



likely to report non-serious crimes (Gove et al., 1985; Klinger and Bridges, 1997; Goudriaan et al., 2006).

For intra-urban spatial and spatiotemporal analyses, call-for-service data are often used because they generally include spatial and temporal details for each reported incident. Official crime data and victimization data, in contrast, include no, or only vague, location and time information. For example, Uniform Crime Reporting Survey datasets summarize the annual number of charged crime offenses for a city or a census tract but infrequently include more precise spatial or temporal information. Likewise, victimization data are collected every five years for national, provincial, or census metropolitan area scales and do not include local spatial or temporal information because samples within smaller areas are not representative (Easton et al., 2014; Perreault, 2015). The spatiotemporal information that is associated with each call-for-service allows researchers to aggregate and analyze data at a range spatial and temporal scales including street blocks or small-areas for years, months, seasons, or days (Sherman et al., 1989; Weisburd et al., 2009; Groff et al., 2010; Andresen and Malleon, 2015; Felson and Boivin, 2015).

Call-for-service data do, however, have a number of limitations. First, and like all types of crime data, call-for-service data are not representative of “real” criminal activity. The decision to report a crime may reflect individual cost-benefit analyses regarding the seriousness of the crime and the effort of reporting, fear of police, a disinterest in police involvement, and perceptions of law enforcement as illegitimate and unresponsive (Kirk and Matsuda, 2011; Kirk and Papachristos, 2011). Related, individuals living in areas with low social cohesion have been shown to be less likely to report crimes, even after controlling for incident- and individual-level characteristics, which indicates that the urban environment influences both crime events and crime reporting (Baumer, 2002; Goudriaan et al., 2006). Second, call-for-service data may have inaccuracies based on unclear incident descriptions, classification errors by police, and the cultural and operational expectations of police agencies regarding the recording of reported incidents (Warner and Pierce, 1993).

Classification errors include false positives, or when a crime is reported that does not exist; false negatives, or when a less serious incident is reported than what actually occurred; and misclassifications of type, or when a robbery is recorded as a burglary, for example (Klinger and Bridges, 1997). Third, multiple calls-for-service may be made for a single incident, leading to inflated counts for events occurring in public spaces or events involving large groups of people (Bursik Jr. et al., 1990; Bursik Jr. and Grasmick, 1993). Fourth, the spatial and temporal information associated with each call-for-service is typically often obscured for confidentiality (e.g., address locations are offset to the nearest intersection or generalized to the nearest street) and reflects the location and time of the caller, rather than the location and time of the true crime event (Sherman et al., 1989; WRPS, 2018b).

### **1.6.3. Describing the crime and disorder data**

The crime and disorder data used in this dissertation was retrieved from the Waterloo Region Police Service (WRPS) call-for-service datasets for five years, from 2011 to 2015 (WRPS, 2018a). These datasets provide information regarding the location, time, and type of police calls-for-service, as well as additional details relevant to police operations (e.g., the priority of the call to police, the units of police service time allocated to the call) (WRPS, 2018b). In all datasets, call-for-service locations were offset from the real location to the closest intersection and intersection data were specified as geographic coordinates (WRPS, 2018b). Note that, in exploring this dataset, it was found that there were more intersection locations in the call-for-service datasets than were in the Statistics Canada road network file because locations in the call-for-service data included locations more precise than street intersections, such as entrances to shopping centres and intersections within parking lots.

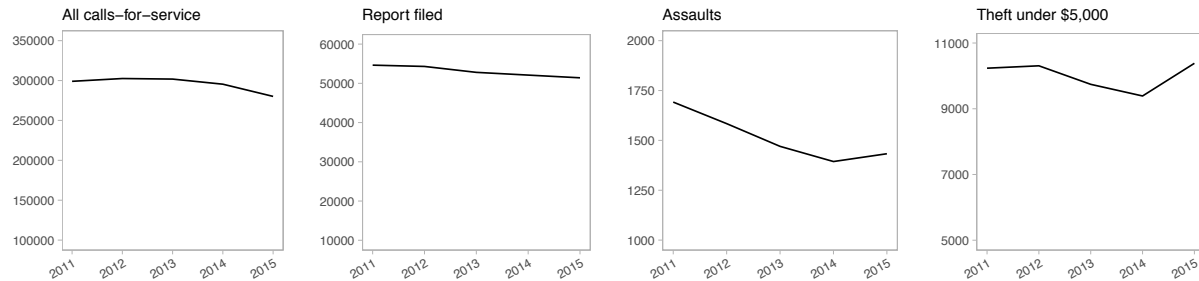
The WRPS data used in this study have a number of features that address the limitations of conventional call-for-service datasets (see Section 1.6.2). First, each dataset included a field that defined the disposition of each call-for-service. This field indicated whether or not a reported incident

was cancelled, was a duplicate, or was serious enough for a police report to be prepared (WRPS, 2018a). Bursik and Grasmick (1993) argue that data confirming whether or not a police report was filed helps to address potential over-reporting of calls-for-service. For this dataset, a relatively small proportion of all calls-for-service had a report filed (e.g., 16.3% of 299,037 incidents in 2011 and 16.1% of 302,533 incidents in 2012). Second, the WRPS data classifies the type of each call-for-service based on the initial description (based on caller description and police interpretation) and the final description (based on further investigation by police) (WRPS, 2018a). In this dissertation, all call-for-service data included in analyses had a report filed, were classified based on the final call type, and were spatiotemporally defined based on the reported location and the reported time in order to best capture the proportion of calls that were “real” crime events along with their types, locations, and times. For the specific crime types used in each research article, see Chapters 2, 3, and 4.

#### **1.6.4. Inspecting the crime and disorder data**

Exploratory data analysis was done to ensure that there were no unusual spatial and/or temporal patterns in the WRPS call-for-service dataset. Temporally, Figure 1.4 shows the total number of calls-for-service, the total number of calls-for-service with a report filed, the total number of assaults (with a report filed), and the total number of thefts under \$5,000 (with a report filed) for each year, from 2011 to 2015. Total calls-for-service and calls-for-service with a police report filed are indicators of the overall level of reported incidents for each year, and assaults and thefts less than \$5,000 were the most common types of violent crime and property crime analyzed in this dissertation, respectively. Total calls-for-service and report-filed calls-for-service showed a relatively stable trend from 2011 to 2015. Assaults decreased by about 15% percent and thefts under \$5,000 increased by about 1% percent over the duration of the five-year study period. These changes are relatively small and generally in line with the regional and national level changes observed in official crime data over this

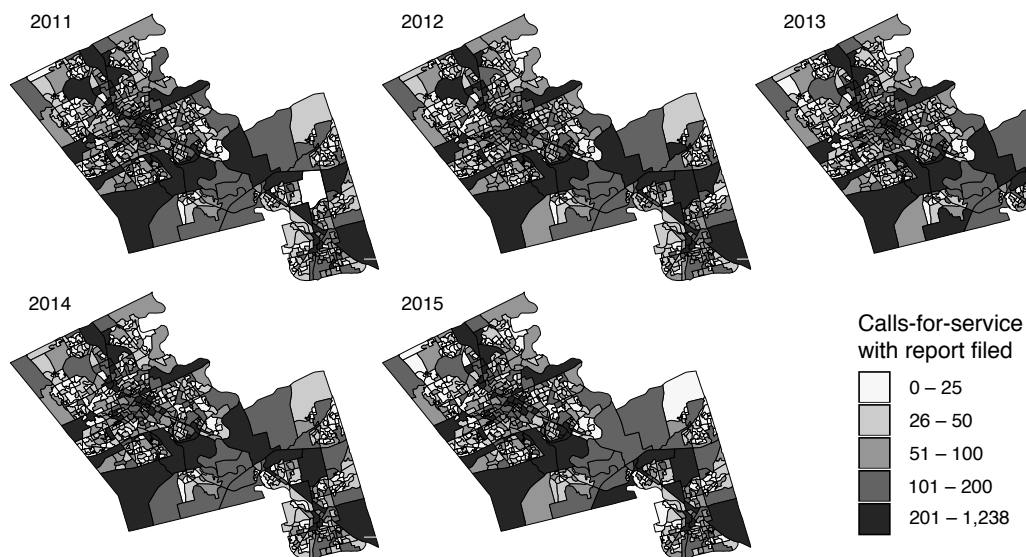
same time period (Allen, 2016). This suggests that any possible changes in operational or reporting procedures did not substantially influence the frequency of calls-for-service between 2011 and 2015.



**Figure 1.4. Counts of total calls-for-service, calls-for-service with a report filed, assaults, and thefts under \$5000 from 2011 to 2015.**

Comparing the year-to-year changes in WRPS reported-call-for-service data with official crime data also indicates that the call-for-service trends generally align with national-, provincial, and regional-level trends. For the Kitchener-Cambridge-Waterloo census metropolitan area, Uniform Crime Reporting survey data shows that total crime, violent crime, and property crime all decreased between 2011 and 2014, and increased in 2015 by 6%, 2% and 7%, respectively (Boyce, 2015; Boyce et al., 2014). A similar pattern was observed in the WRPS call-for-service data, where total report-filed calls-for-service, assaults, and thefts under \$5,000 exhibited decreasing trends from 2011 to 2014. For the province of Ontario, total police-reported crimes, property crimes, and violent crimes in the province of Ontario decreased between 2011 and 2014 and increased by about two percent, zero percent, and one percent in 2015 (Allen, 2016). At the national-level, total crimes, violent crimes, and property crimes also decreased between 2011 and 2014 and increased in 2015 by 3%, 2%, and 4%, respectively (Allen, 2016). The trends observed in the WRPS call-for-service data most closely paralleled the regional UCR statistics, which suggests that, while calls-for-service are more frequent than official crimes, the data analyzed in this dissertation did not depart from the general trends reported by the police to Statistics Canada.

Spatially, maps of the total calls-for-service with a report filed for each year were examined to inspect for substantial differences in annual crime counts. Figure 1.5 maps the total count of incidents with a report filed for each year (2011 to 2015) at the dissemination area scale for the cities of Cambridge, Kitchener, and Waterloo. In general, the spatial patterns of total call-for-service counts were consistent during the time period, with high counts located along the central commercial corridor connecting Waterloo, Kitchener, and Cambridge (see Appendix A for a detailed map of the study region). The similarities observed between years was supported by positive Kendall's  $\tau_B$  correlation coefficients between annual total call-for-service counts for all adjacent years (all  $\tau_B$ 's > 0.75). This indicates that there were no unusual differences in within-area crime counts between years that may be indicative of changes to data collection or data handling procedures.



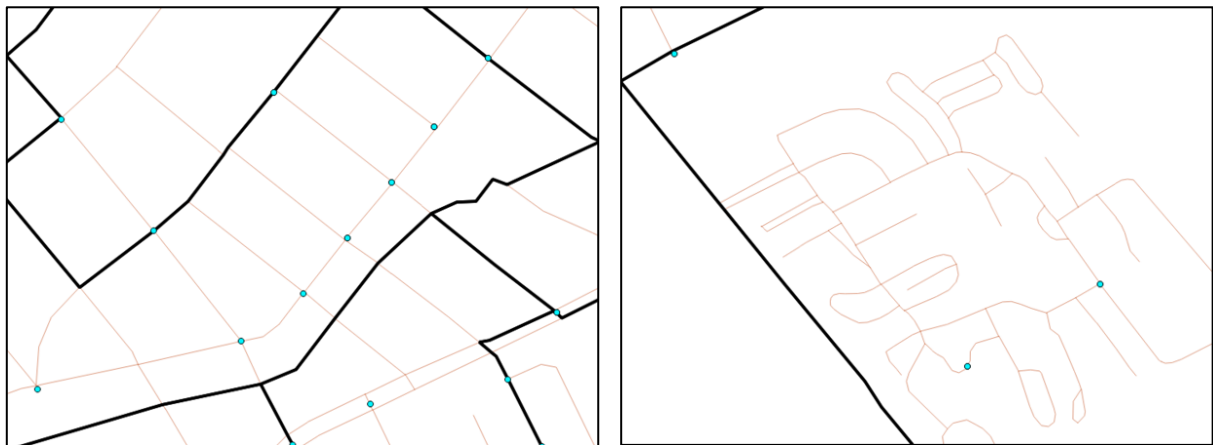
**Figure 1.5. Call-for-service counts (with report filed) at the dissemination area level.**

In this dissertation, call-for-service locations were aggregated from intersections to dissemination areas (DAs) for analysis. For reference, DAs are delineated by Statistics Canada and have residential populations that are approximately between 400 and 700 (Statistics Canada, 2015).

Call-for-service intersection data was aggregated to DAs for three reasons. First, dissemination areas are the smallest areal unit for which census data was available from Statistics Canada. This allows for the integration of social, economic, and demographic data, built environment data, and crime and disorder data at one common spatial unit of analysis. Second, DAs or similarly sized areas have been used to conceptualize and analyze both neighbourhood effects and opportunity theories of crime (Shaw and McKay, 1942; Bursik et al., 1990; Sampson et al., 2002; Sampson, 2013; Andresen, 2006b; Bannister et al., 2017). Note, however, that the geographic areas used for this analysis, and in any study using politically defined boundaries, are unlikely to reflect the spatial, social, and functional extents of individual or collective behaviours (Galster, 2001; Sampson, 2012; Bannister, 2017). Third, aggregating call-for-service data to DAs reduces potential location misclassification insofar as both the location of the caller and the nearest intersection were located within the same small-area (Warner and Pierce, 1993). There are no theoretical or data-driven reasons to believe that the prevalence of calls-for-service was related to the number of intersections within a DA, in and of itself, after accounting for population size. As such, population size was included as a covariate in all research articles.

Exemplifying the integration of call-for-service data with the DAs, two maps of violent crime points superimposed on streets and DA boundaries are shown in Figure 1.6. This visualization illustrates one limitation of the data aggregation approached used in this dissertation, and one of the major limitations of this dissertation, in general: that it is possible for some calls-for-service to have been located within one DA but assigned to an adjacent DA when aggregating from points to areas. This is discussed further in Section 5.3. For example, approximately 50% of all unique intersections in the call-for-service dataset were located within 30 meters of a DA boundary. This includes relatively small DAs (with many intersections close to area boundaries) in the city centre and relatively large DAs (also with many intersections but with fewer close to the boundaries) in more suburban areas. (Figure 1.6) Also, it is important to note that this limitation is not unique to this

dataset or this data aggregation approach, but are common issues when point data is aggregated to areas. Analytically, some of the possible data misclassification between DAs was captured by the spatially structured random effects terms (in Chapters 2 and 3) and by the higher-level random effects terms (in Chapter 4). These terms impose spatial smoothing of modeled crime counts between adjacent areas and would reduce the effect of one DA being assigned an extremely high or low count of crime or disorder due to the intersection locations.



**Figure 1.6. Violent crime calls-for-service (points), streets (orange), and DA boundaries (black) in an urban area (left) and a suburban area (right).**

### **1.6.5. Census data**

In Chapter 2 and 3, variables measuring the social, economic, and demographic characteristics of dissemination areas were retrieved from the 2011 National Household Survey (NHS) and the 2011 Canadian census. In Chapter 4, social, economic, and demographic data were retrieved from the 2016 Canadian census. Given the limitations of the 2011 NHS due to changes in sampling strategy and the potential for non-response bias (Smith, 2015), data from the 2011 NHS was checked against census data from the 2006 and 2016 censuses and few substantive differences were observed.

Fifteen DAs in the study region had missing data for one or more social, economic, or demographic variables in the NHS, or less than three percent of areas in the study region. In the 2016

census, thirteen DAs in the study region had missing data for one or more explanatory variables, or less than two percent of all areas. All missing census data was treated as unknown and was imputed using Bayesian spatial models. In Chapters 2 and 3, the imputed missing data was entered as a point estimate and treated as known in the spatiotemporal analyses of crime. In Chapter 4, the missing data was imputed and included in the spatiotemporal crime models under one Bayesian framework (i.e., the uncertainty associated with the imputed data was propagated to the crime model; see Appendix I).

#### **1.6.6. Built environment data**

Built environment data measuring land use composition within DAs was analyzed in Chapters 2, 3, and 4. This data was collected from the Region of Waterloo, a vector database of land use parcels for primary land use types (DMTI Spatial Incorporated, 2011), and Statistics Canada via the North American Industry Classification System (NAICS). In Chapters 2, 3 and 4, the central business districts of the three cities in the study region were defined based on municipal business improvement area boundaries. In Chapter 3, polygonal land use data from the Region of Waterloo and the DMTI vector land use database were intersected with DA boundaries and assigned a binary indicator or a density measure (see Section 3.4). Point land use data from the Statistics Canada NAICS was aggregated to DA boundaries using a point-in-polygon approach and assigned a binary indicator.

#### **1.7. Summary of Chapters**

In this introductory chapter, I have highlighted why understanding the relationships between crime and the urban environment is important, outlined the objectives of this dissertation, described a theoretical framework for explaining the intra-urban spatiotemporal patterning of crime, illustrated the connections between crime and planning, and examined the call-for-service data used in each research article. The three research articles in Chapters 2, 3, and 4 make up the body of this dissertation: Chapter 2 examines the shared and type-specific spatiotemporal patterning of physical



disorder, social disorder, property crime, and violent crime; Chapter 3 investigates the time-varying relationships between land use and seasonal property crime trends; and Chapter 4 examines the multiscale spatiotemporal patterning of violent crime for small-areas, planning neighbourhoods, electoral wards, and police patrol zones. In Chapter 5, I summarize the results of the three research articles; reflect on the theoretical, analytical, and policy contributions of this dissertation; highlight limitations of this research; and identify directions for future study.

## **Chapter 2: Spatiotemporal modelling of correlated small-area outcomes: Analyzing the shared and type-specific patterns of crime and disorder<sup>1</sup>**

### **2.1. Summary**

This research applies a Bayesian multivariate modelling approach to analyze the spatiotemporal patterns of physical disorder, social disorder, property crime, and violent crime at the small-area scale. Despite crime and disorder exhibiting similar spatiotemporal patterns, as hypothesized by broken windows and collective efficacy theories, past studies often analyze a single outcome and overlook the correlation structures between multiple crime and disorder types. Accounting for five covariates, the best-fitting model partitions the residual risk of each crime and disorder type into one spatial shared component, one temporal shared component, and type-specific spatial, temporal, and space-time components. The shared components capture the underlying spatial pattern and time trend common to all types of crime and disorder. Results show that population size, residential mobility, and the central business district are positively associated with all outcomes. The spatial shared component is found to explain the largest proportion of residual variability for all types of crime and disorder. Spatiotemporal hotspots of crime and disorder are examined to contextualize broken windows theory. Applications of multivariate modelling with shared components to ecological crime theories and crime prevention policy are discussed.

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<sup>1</sup> The citation for this article is Quick, M., Li, G., and Law, J. (2018). Spatiotemporal modelling of correlated small-area outcomes: Analyzing the shared and type-specific patterns of crime and disorder. *Geographical Analysis*. DOI: 10.1111/gean.12173.

## 2.2. Introduction

Quantitative methods for spatial and spatiotemporal data generally analyze one outcome or dependent variable. Spatial methods for analyzing a single crime type at the small-area scale include mapping of crime rates, spatial regression models, and clustering algorithms such as local Moran's I and Getis-Ord  $G_i$  and  $G_i^*$  statistics (Ratcliffe and McCullagh, 1999; Anselin et al., 2000). To examine spatiotemporal crime change, studies have compared spatial crime clusters and/or the results of cross-sectional regression methods across two or more time periods (Frazier et al., 2013; He et al., 2017) and have used methods that analyze both geographic and temporal dimensions of a single crime type, including space-time interaction tests for point data, the space-time scan statistic for point and areal data, and generalized linear mixed models for areal data with spatial and temporal structure (Johnson and Bowers, 2004; Shiode and Shiode, 2014; Chun, 2014; Li et al., 2014).

Distinguishing the similarities and differences between the spatiotemporal patterns of multiple crime types is fundamental to theoretical development and crime prevention policy. If, for example, violent crime and property crime exhibit similar patterns, then both crime types may be associated with the same set of risk factors and explained by a generalizable theory (Weisburd et al., 1993). But if patterns are dissimilar, then crime prevention strategies should be designed for each type and type-specific theoretical explanations pursued (Haberman, 2017). Studies examining the patterns of multiple crime types often compare the results of separate analyses of a single crime type (e.g., the Knox test in Grubestic and Mack (2008) and the space-time scan statistic in Leitner and Helbich (2011)), however this approach does not account for the correlations between crime types or identify the patterns shared amongst two or more crime types.

Focusing on the spatiotemporal correlations between crime and disorder, broken windows theory contends that physical and social disorder, or physical signs of deterioration and unsettling behaviours, respectively, lead to increases in property crime and violent crime (Kelling and Wilson,

1982). As one of the most influential and controversial ideas in urban sociology and criminology, broken windows theory has widely impacted urban planning policy and policing strategies that prioritize disorder reduction as a way to prevent crime (Harcourt and Ludwig, 2006). In contrast, collective efficacy theory proposes that crime and disorder are associated with the same underlying social processes but does not hypothesize that increases in disorder precede increases in crime (Sampson et al., 1997; Sampson and Raudenbush, 1999). While past research has shown that crime and disorder are correlated within neighborhoods (Skogan, 1990; Taylor, 2001; Yang, 2010), few studies have investigated how local patterns of crime and disorder change over time, explored if crime and disorder share one or more spatial or temporal patterns, or examined the degree to which disorder precedes crime at the small-area scale (Boggess and Maskaly, 2014; Shiode and Shiode, 2014).

This research applies a Bayesian multivariate modelling approach to analyze the spatiotemporal patterns of physical disorder, social disorder, property crime, and violent crime over five years at the small-area scale. Multivariate models simultaneously analyze multiple dependent variables and can accommodate data that are correlated between nearby areas, between adjacent time periods, and between outcomes. For dependent variables that have similar data-generating processes, multivariate models provide a framework for estimating shared components (or latent factors) that capture the spatial and/or temporal structure common to two or more of the dependent variables (Knorr-Held and Best, 2001; Richardson et al., 2006). In this study, three models with various assumptions regarding the spatial and temporal correlation structures between the four types of crime and disorder are compared. The best-fitting model accounts for five demographic, socioeconomic, and built environment characteristics, and partitions the residuals of each crime and disorder type into one spatial shared component, one temporal shared component, and type-specific spatial, temporal, and space-time components. The spatial shared component is found to explain the largest proportion of residual variability for all types of crime and disorder.

Following this introduction, methods for analyzing the spatiotemporal patterns of a single crime type are reviewed and broken windows, collective efficacy, and routine activity theories are outlined. Next, the data are described, three multivariate spatiotemporal models are detailed, and the best-fitting model is identified. Results are visualized and interpreted, and the implications of this research for spatiotemporal analysis of small-area data, for ecological crime theories, and for crime prevention policy are discussed.

### **2.3. Methods for analyzing spatiotemporal crime patterns**

Quantitative methods for analyzing spatiotemporal data can be grouped into three categories: space-time interaction tests, exploratory cluster detection techniques, and spatiotemporal modelling approaches (Robertson et al., 2010). Space-time interaction tests measure the clustering of a single outcome by comparing the observed number of point pairs that occur nearby in both space and time to the entire distribution of point pairs (Rey et al., 2012). The Knox test, for example, uses researcher-specified distance and time values to define space-time interaction, and has been applied to characterize the clustering of burglary, robbery, and assault, and to identify the distance and time thresholds indicative of repeat victimization (Knox and Bartlett, 1964; Grubestic and Mack, 2008). Space-time interaction tests are univariate and can be used to identify point pairs located within a given distance and time, but are not suitable for analyzing data aggregated at the small-area scale, multiple correlated outcomes, or covariates that may explain crime risk (Kim and O’Kelly, 2008; Shiode and Shiode, 2014).

#### **2.3.1. Cluster detection techniques**

Cluster detection techniques identify groups of points or areas with high or low crime (Anselin et al., 2000). Like space-time interaction tests, conventional cluster detection methods analyze one outcome and do not accommodate covariates. Three of the most popular local cluster detection methods

applied to crime data are local Moran's I and Getis-Ord  $G_i$  and  $G_i^*$  statistics, all of which calculate an index of local spatial autocorrelation relative to a null hypothesis of spatial randomness for one time period (Getis and Ord, 1992; Anselin et al., 2000; Fotheringham, 2009). The spatial scan statistic also identifies points or areas with high crime by using a scanning window to calculate a test statistic based on observed and expected crime risk both within and outside of the scanning window (Kulldorff et al., 1998). While local Moran's I, Getis-Ord  $G_i$  and  $G_i^*$  statistics, and the spatial scan statistic are cross-sectional, they have been applied across multiple time periods to explore how the locations of violent crime and disorder hotspots change over time (Ceccato and Haining, 2004; Frazier et al., 2013; He et al., 2017).

Incorporating spatial and temporal information, the space-time scan statistic uses a scanning window with varying radii (space) and heights (time) to identify crime clusters for at least two time periods (Kulldorff et al., 1998). The space-time scan statistic has been used to explore seasonal violent crime clusters, monthly theft hotspots, and the impacts of a major hurricane on the location and duration of burglary and auto theft hotspots (Ceccato, 2005; Kim and O'Kelly, 2008; Nakaya and Yano, 2010; Leitner and Helbich, 2011). The space-time scan statistic has been adapted to accommodate network distances to better identify crime clusters at the address-level (Shiode and Shiode, 2014). Also exploring the space-time patterns of one crime type, Rey et al. (2012) develop a spatial Markov chain to estimate the probability that an area will experience a crime event at a future time period conditional on initial levels of crime in immediate and adjacent areas. Kerry et al. (2010) apply geostatistical methods, including area-to-area and area-to-point kriging, to produce continuous maps of crime risk from point data and generate area-based risk estimates for inputs into spatial regression models.

### 2.3.2. Spatiotemporal modeling approaches

Within the generalized linear mixed modeling framework (Breslow and Clayton, 1993), spatiotemporal modelling approaches analyze the associations between dependent and independent variables and include additional model terms to account for residual spatial and temporal structure (Waller et al., 1997; Chun, 2014). Spatiotemporal models used in past crime research have predominately analyzed one crime type as the dependent variable. In the frequentist statistical framework, one technique to account for spatial autocorrelation is eigenvector spatial filtering (ESF), which uses orthogonal and uncorrelated eigenvectors decomposed from spatial weights matrices to create a set of parameters with different spatial structures (Getis and Griffith, 2002; Tiefelsdorf and Griffith, 2007). Chun (2014) analyzes vehicle burglary over five years at the small-area scale, fitting Poisson and negative binomial regression models with ESF and autoregressive random effects to account for spatial and temporal structure, respectively. Exploring nonviolent crimes over five years, Helbich and Arsanjani (2015) also use Poisson and negative binomial regression models with ESF and compare the models constructed for each time period to identify the eigenvectors that best account for global, regional, and local spatial patterns.

In the Bayesian statistical framework, residual spatial, temporal, and spatiotemporal structure is typically specified via prior distributions for random effects parameters. Briefly, Bayesian hierarchical models combine observed data and prior information (e.g., spatial and/or temporal adjacency) to estimate full probability distributions for model parameters. For small-area data, the most common prior distribution used to model residual spatial structure is the intrinsic conditional autoregressive distribution (ICAR), which borrows information from nearby areas to estimate a spatially smoothed risk surface (Besag et al., 1991; see Section 5.1). With a temporal adjacency matrix, the ICAR prior distribution has also been applied to model non-linear time trends (Richardson et al., 2006; Quick et al., 2017). Past studies applying Bayesian spatiotemporal models to small-area

crime data have analyzed violent crime and property crime over two years (Law et al., 2014; Law et al., 2015), burglary over four- and eight-year time periods (Li et al., 2013; Li et al., 2014), and police confidence over 36 quarters (Williams et al., 2018). Quick et al. (2018) use a Bayesian multivariate model to analyze burglary, robbery, vehicle crime, and violent crime, and identify one crime-general spatial pattern shared amongst all crime types and a second crime-general spatial pattern shared amongst the three theft-related crimes.

## **2.4. Spatiotemporal theories of crime and disorder**

Spatiotemporal patterns of crime and disorder are most commonly explained by broken windows and collective efficacy theories. Broken windows theory hypothesizes that high levels of physical and social disorder increase fear of crime amongst residents, signal to offenders that residents will not intervene in criminal behaviour, and lead to increases in both property crime and violent crime over time (Kelling and Wilson, 1982; Markowitz et al., 2001; Xu et al., 2005; Gau et al., 2014). By outlining the pathway from disorder to crime, and because disorder has been shown to be an important factor shaping community stability and quality of life, broken windows theory has widely influenced urban policy (Skogan, 1990; Sampson and Raudenbush, 2004). Policing applications of broken windows theory include order-maintenance strategies that issue citations and arrests for non-criminal disorder incidents, such as loitering, panhandling, and graffiti (Ranasinghe, 2011; Gau et al., 2014).

Broken windows theory as applied to planning originates from Jacobs' (1961) observations that public space shapes perceptions of order/disorder and safety, and that civility in public space is necessary for healthy city functioning (Ranasinghe, 2011). Examining the implications of disorder on neighbourhood social-spatial processes of change, Skogan (1986; 1990) suggests that disorder leads to disinvestment in physical infrastructure and housing, increases in urban inequality that result from selective out-migration of affluent households from high disorder areas, and suppression of real estate



prices that contribute to neighbourhood decline (Markowitz et al., 2001). The link between disorder and crime has also been used to justify urban policies that aim to improve community safety and enhance the urban experience for some residents (Gau et al., 2014). For example, Ontario's Safe Streets Act (1999), which banned squeegeeing and aggressive panhandling, was upheld in the Ontario Court of Appeal on the basis that these forms of social disorder can reduce the health of urban areas (Ranasinghe, 2011; R vs. Banks, 2007). Directly pertaining to urban planning are policies that require immediate remediation or demolition of abandoned buildings and vacant lots and by-laws that mandate the immediate removal of graffiti on public or private property (Sampson and Raudenbush, 2004; Harcourt and Ludwig, 2006; Hinkle and Weisburd, 2008; Kohm, 2009). Business Improvement Districts, which are organizations that provide security, maintenance, and aesthetics in exchange for a fee from constituent businesses, also have connections to broken windows theory as one of their functions is to remove signs of physical and social disorder in order to increase perceptions of safety, reduce crime, and increase business by making commercial areas more appealing to consumers (Hoyt, 2005; Vindevogel, 2005).

Shifting focus to the social dynamics within neighbourhoods, collective efficacy theory proposes that crime and disorder both result from low social cohesion and low informal social control (Sampson et al., 1997; Sampson and Raudenbush, 1999). Neighborhoods with low social cohesion and low informal social control, as operationalized by high socioeconomic disadvantage, high residential mobility, and high ethnic heterogeneity, are thought to exhibit high levels of crime and disorder because residents are ineffective at establishing and realizing common goals, such as living in a safe and orderly neighborhood (Sampson and Groves, 1989; Sampson et al., 1997; Laurence, 2017). Importantly, collective efficacy theory challenges the central tenet of broken windows theory that increases in disorder precede increases in crime and, instead, collective efficacy theory argues that crime and disorder are associated with the same underlying social processes and neighborhood conditions (Sampson and Raudenbush, 2004; Harcourt and Ludwig, 2006).

Despite the tensions between broken windows and collective efficacy theories being inherently spatiotemporal, past research has predominantly examined the relationships between one type of crime or disorder (as a single dependent variable) and other types of crime and disorder (as independent variables) for one time period (e.g., Sampson and Raudenbush, 2004; Cerda et al., 2009). Spatiotemporal analyses have observed that crime and disorder generally exhibit similar patterns (Doran and Lees, 2005; Yang, 2010; Boggess and Maskaly, 2014), however no study has explored if crime and disorder share an underlying spatial pattern, as hypothesized by collective efficacy theory, or investigated the degree to which disorder precedes crime at the small-area scale, as anticipated by broken windows theory.

In addition to broken windows and collective efficacy theories, intra-urban patterns of crime and disorder have been interpreted using routine activity theory. Routine activity theory hypothesizes that crime events occur when suitable targets, motivated offenders, and a lack of capable guardianship converge in space and time (Cohen and Felson, 1979). By highlighting how the spatiotemporal distribution of suitable targets influences crime patterns, routine activity perspectives recognize that crime and disorder may be correlated in areas with many target types, such as in central business districts where both material goods for property crime and large populations for violent crimes are concentrated, but that crime and disorder may not be correlated in areas with only one target type, such as around a shopping mall where the number of property crime targets is likely greater than the number of violent crime targets.

## **2.5. Study region and data**

The Region of Waterloo is composed of three municipalities (Cambridge, Kitchener, and Waterloo) and is located approximately 100 km west of Toronto, Ontario, Canada. The geographic unit of analysis was the census dissemination area (DA). DAs are the smallest areal unit that cover the entirety of Canada and are delineated such that residential populations are between 400 and 700. In

the 2011 census there were 655 DAs in the study region with an average size of 0.49 km<sup>2</sup>. A detailed map of the study region is shown in Appendix A.

Reported incident data for physical disorder, social disorder, property crime, and violent crime were obtained from Waterloo Regional Police Services for five years, from 2011 to 2015. Reported incidents were aggregated from street intersections to small-areas. Reported incident data are commonly used to measure both crime and disorder at the small-area scale (Braga and Bond, 2008; Yang, 2010). Physical disorder counts were the sum of property damage and graffiti incidents, and social disorder counts were the sum of drug, public mischief, public disturbance, indecent act, and intoxicated person incidents (Skogan, 1990; Hinkle and Weisburd, 2008). Property crime counts were the sum of break and enter, theft under \$5,000, theft over \$5,000, and motor vehicle theft incidents. Violent crime counts were the sum of assault and robbery incidents. In total, there were 10,005 incidents of physical disorder, 12,338 incidents of social disorder, 46,856 property crimes, and 6,812 violent crimes. Descriptive statistics for the four types of crime and disorder are shown in Table 2.1.

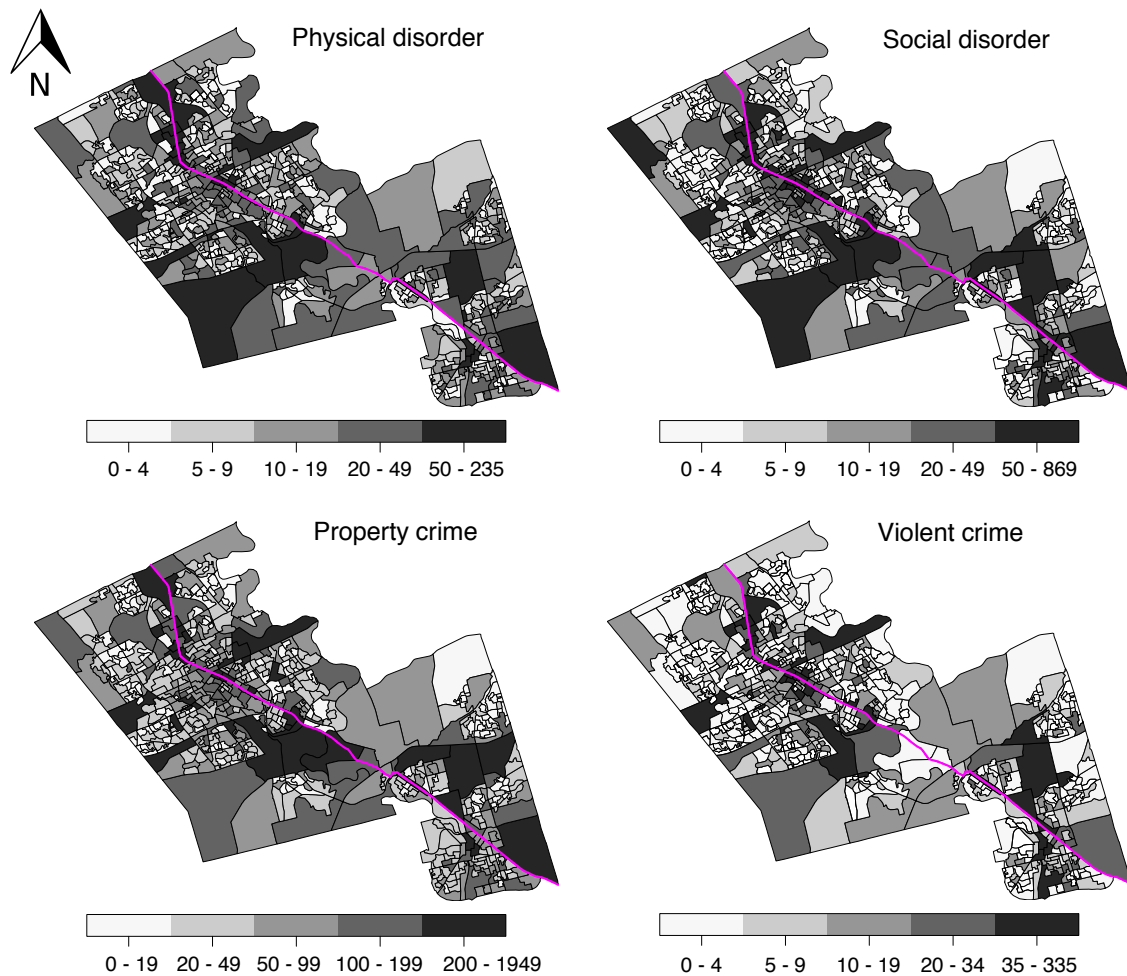
**Table 2.1. Descriptive statistics for total counts of crime and disorder and for five explanatory variables.**

	Mean	SD
Crime and disorder types		
Physical disorder	15.27	21.37
Social disorder	16.84	47.97
Property crime	71.46	135.13
Violent crime	10.40	21.23
Explanatory variables		
Population	678.90	478.96
Residential mobility (%)	38.15	17.51

Low-income households (%)	12.61	11.69
Ethnic heterogeneity (0 to 1)	0.31	0.15
Central business district	0.02	NA <sup>a</sup>

<sup>a</sup> Standard deviation not reported for binary variables

Total counts of physical disorder, social disorder, property crime, and violent crime are mapped in Figure 2.1. In general, areas with high counts of all types of crime and disorder were located along the central commercial corridor as well as in the southwest and southeast of the study region. Comparing between types, areas with high counts of violent crime were concentrated in close proximity to the central commercial corridor, whereas areas with high counts of physical disorder, social disorder, and property crime were relatively more dispersed.

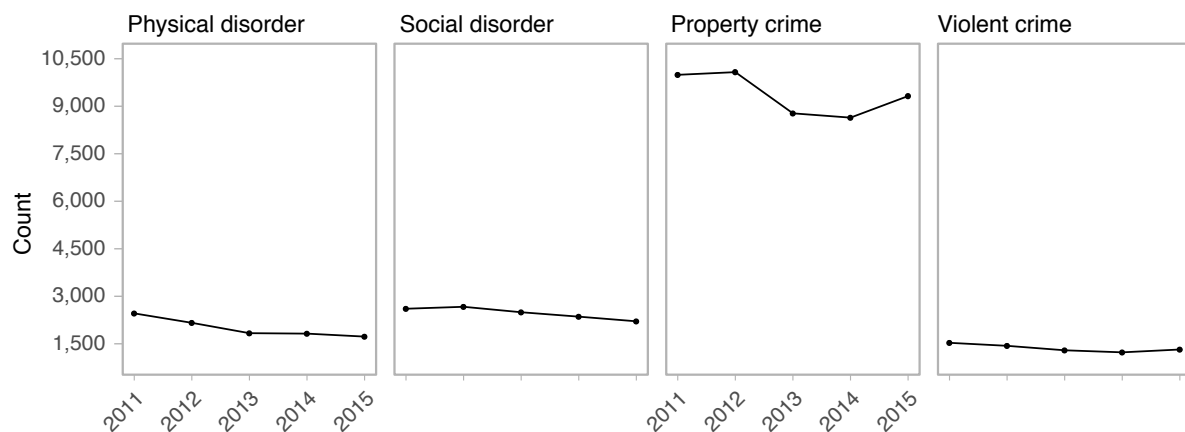


**Figure 2.1. Total counts of physical disorder, social disorder, property crime, and violent crime. The central commercial corridor is highlighted.**

Pairwise correlations between all types of crime and disorder were positive. This supports the visual similarities observed between crime and disorder maps (Figure 2.1). Social disorder and violent crime exhibited the strongest positive correlation (Kendall's  $\tau_b = 0.70$  and Pearson's  $r = 0.93$ ) while the weakest positive correlations were between violent crime and property crime (Kendall's  $\tau_b = 0.60$  and Pearson's  $r = 0.62$ ) and between violent crime and physical disorder (Kendall's  $\tau_b = 0.61$  and Pearson's  $r = 0.58$ ). All types of crime and disorder were spatially autocorrelated as per a first-order queen contiguity spatial weights matrix ( $p < 0.05$ ): social disorder had the highest spatial

autocorrelation (Moran's I = 0.28), followed by violent crime (0.23), physical disorder (0.21), and property crime (0.14). Annual pairwise correlation coefficients and Moran's I values are shown in Appendix B.

Crime and disorder trends over the five-year study period are shown in Figure 2.2. In general, all types of crime and disorder decreased between 2011 and 2015, with physical disorder and social disorder showing modest and consistent declines across all years. Property crime increased slightly from 2011 to 2012, decreased during the third and fourth years, and increased by eight percent during the final year. Violent crime decreased by about 20% from 2011 to 2014 and increased by seven percent from 2014 to 2015.



**Figure 2.2. Annual counts of physical disorder, property crime, social disorder, and violent crime from 2011 to 2015.**

Five explanatory variables operationalizing population size, socioeconomic context, and the built environment were included in the analyses (Table 2.1). Following Ceccato et al. (2018), residential population was included as an explanatory variable for two reasons. One, because there was no clear population at risk for the four types of crime and disorder. Two, because assuming that population size and crime/disorder are positively associated, which is implied when using residential population to derive crime/disorder rates (for continuous regression models) or offset terms (for count regression models), may not be appropriate as past research has shown that crime/disorder often

cluster in areas with small residential populations, such as in the central business district (Malleon and Andresen, 2015). Note that conceptualizing and measuring the population at risk in spatiotemporal analyses of crime/disorder is challenging because offenders and targets are mobile and because quantitative estimates of populations or crime targets are often not available (e.g., daytime populations) or accurately inferred using existing data at the small-area scale (e.g., the number of targets within a store).

The socioeconomic context of small-areas was operationalized via five-year residential mobility, the percent of low-income households, and the index of ethnic heterogeneity<sup>2</sup> (Sampson et al., 1997; Sturgis et al., 2014). These three variables are often used to characterize the structural dimensions of collective efficacy and have been found to be associated with crime and disorder at the small-area scale (Hinkle and Weisburd, 2008; Boggess and Maskaly, 2014). The central business districts (CBD) of the three municipalities were operationalized using a binary variable, where DAs within the CBDs were assigned a value of one and all other DAs were assigned a value of zero. This follows past research finding that crime and disorder incidents both cluster in and around the CBD (Sampson and Groves, 1989; Doran and Lees, 2005; Nelson et al., 2001). Residential population, residential instability, ethnic heterogeneity, and low-income household variables were standardized for analysis.

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<sup>2</sup> The index of ethnic heterogeneity for area  $i = 1 - \sum h_{iz}^2$ , where  $h_{iz}$  is the number of people of ethnicity  $z$  in area  $i$  divided by the total population in area  $i$ . The index of ethnic heterogeneity ranges between zero and one. Higher values of the index of ethnic heterogeneity indicate greater heterogeneity.

## 2.6. Multivariate spatiotemporal modelling of crime and disorder

Counts of each type of crime and disorder are denoted as  $O_{ijk}$ , where  $i$  indexes areas ( $i = 1, \dots, 655$ ),  $j$  indexes year ( $j = 1, \dots, 5$ ), and  $k$  indexes type ( $k = 1, \dots, 4$ ). We assume that  $O_{ijk}$  are independent Poisson variables conditional on mean  $\mu_{ijk}$ ;  $O_{ijk} \sim \text{Poisson}(\mu_{ijk})$ . The Poisson distribution is often used for Bayesian spatiotemporal modelling of small-area count data, where overdispersion and residual spatial and temporal correlations are accounted for via random effects parameters (Breslow and Clayton, 1993; Richardson et al., 2004; Haining et al., 2009).

Model 2–1 assumes no correlations between the four types of crime and disorder and models the Poisson means ( $\mu_{ijk}$ ) as the sum of a type-specific intercept ( $\alpha_k$ ), type-specific covariates for residential population, residential mobility, low-income households, ethnic heterogeneity, and the CBD ( $\beta_{nk}x_{ni}$ ), a set of type-specific spatial random effects terms ( $s_{ik}$ ), a set of type-specific temporal random effects terms ( $\gamma_{jk}$ ), and a set of type-specific space-time random effects terms ( $\theta_{ijk}$ ). For the five covariates ( $n = 1, \dots, 5$ ), the type-specific regression coefficients are represented by  $\beta_{nk}$  and the data for explanatory variable  $n$  in area  $i$  is represented by  $x_{ni}$ . For each type of crime and disorder, the residual spatial pattern is captured by  $s_{ik}$ 's and the time trend is captured by  $\gamma_{jk}$ 's. The space-time random effects terms capture extra-Poisson variability not accounted for via other model parameters and allow for the modeled counts of crime and disorder for each area and time period to depart from the stable spatial and temporal components ( $s_{ik}$  and  $\gamma_{jk}$ ).

$$\log(\mu_{ijk}) = \alpha_k + \beta_{nk}x_{ni} + s_{ik} + \gamma_{jk} + \theta_{ijk} \quad (2-1)$$

Model 2–2 adds a spatial shared component for all types of crime and disorder and assumes that physical disorder, social disorder, property crime, and violent crime residuals share a common spatial pattern (MacNab, 2010). This is supported by visual similarities between maps of crime and disorder (Figure 2.1), positive pairwise correlations between all outcomes (Appendix B), and



collective efficacy theory, which hypothesizes that crime and disorder are associated with the same geographically-varying social processes. The spatial shared component includes four type-specific factor loadings ( $\lambda_k$ ) and a set of spatially structured random effects terms ( $f_i$ ) (Knorr-Held and Best, 2001; Tzala and Best, 2008). The factor loadings allow each type of crime and disorder to have a unique association with the spatial pattern shared amongst all crime and disorder types ( $f_i$ ). Type-specific spatial patterns that diverge from the shared spatial pattern are captured by  $s_{ik}$ 's.

$$\log(\mu_{ijk}) = \alpha_k + \beta_{nk} x_{ni} + (\lambda_k \cdot f_i) + s_{ik} + \gamma_{jk} + \theta_{ijk} \quad (2-2)$$

Model 2–3 adds a temporal shared component that captures the underlying time trend common to all four types of crime and disorder. A shared time trend was anticipated because all types of crime and disorder decreased over the five-year study period (Figure 2.2). The temporal shared component is the product of four type-specific temporal factor loadings ( $\phi_k$ ) and a set of temporally structured random effects terms ( $t_j$ ). Like the spatial shared component, the temporal factor loadings quantify the relative association between each type of crime and disorder and the underlying shared time trend ( $t_j$ ). Type-specific time trends that diverge from the shared trend are captured by  $\gamma_{jk}$ .

$$\log(\mu_{ijk}) = \alpha_k + \beta_{nk} x_{ni} + (\lambda_k \cdot f_i) + (\phi_k \cdot t_j) + s_{ik} + \gamma_{jk} + \theta_{ijk} \quad (2-3)$$

### 2.6.1. Prior distributions

In Bayesian modelling, all parameters are treated as random variables and assigned prior distributions. The type-specific intercepts ( $\alpha_k$ ) were each assigned improper uniform prior distributions (Thomas et al., 2004). The type-specific regression coefficients ( $\beta_{nk}$ ) were each assigned a normal distribution with a mean of zero and variance of 1,000.

Random effects terms  $f_i$ ,  $t_j$ ,  $s_{ik}$ ,  $\gamma_{jk}$ , and  $\theta_{ijk}$  model the shared and type-specific spatial, temporal, and space-time structure of residuals after controlling for covariates. All random effects terms are estimated from the data. For the space-time random effects terms ( $\theta_{ijk}$ ), a centered

parameterization was used to fit the models such that  $\log(\mu_{ijk}) \sim \text{Normal}(\eta_{ijk}, \delta_{\theta_k}^2)$ , where  $\eta_{ijk} = \alpha_k + \beta_{nk}x_{ni} + (\lambda_k \cdot f_i) + (\phi_k \cdot t_j) + s_{ik} + \gamma_{jk}$  (for Model 3) and where  $\theta_{ijk} = \log(\mu_{ijk}) - \eta_{ijk}$  (Tzala and Best, 2008; Appendix E). This is equivalent to specifying  $\theta_{ijk}$  as a set of unstructured random effects terms assigned normal prior distributions with means of zero and type-specific variances  $\delta_{\theta_k}^2$ . Centered parameterizations of generalized linear mixed models have been shown to improve convergence of random effects parameters fitted via Markov chain Monte Carlo (MCMC) algorithms (Gelfand et al., 1995).

The type-specific spatial random effects terms ( $s_{ik}$ ) were assigned ICAR prior distributions with type-specific variances  $\delta_{s_k}^2$ . This prior assumes that crime and disorder residuals exhibit positive local spatial autocorrelation. In the ICAR distribution, each  $s_{ik}$  is normally distributed with the mean equal to the average of the means of  $s_{ik}$ 's in nearby areas (Besag et al., 1991). Spatial weights matrix  $W$  was used to define spatial adjacency for the ICAR prior distribution, where  $W_{ii} = 0$ ,  $W_{ic} = 1$  if area  $i$  is adjacent to area  $c$ , and  $W_{ic} = 0$  otherwise (i.e., first-order queen contiguity matrix). The conditional variances of the posterior distributions of  $s_{ik}$ 's are equal to  $\delta_{s_k}^2 / n_i$ , where  $n_i$  is the number of areas adjacent to area  $i$ , as defined in  $W$ . This assumes that areas with many neighbors will have more precise estimates of  $s_{ik}$  than areas with few neighbors (Besag et al., 1991).

In Models 2–2 and 2–3, the spatially structured random effects terms in the spatial shared component ( $f_i$ ) were assigned ICAR prior distributions with the variance fixed to one (Hogan and Tchernis, 2004; Richardson et al., 2006; Tzala and Best, 2008). Because estimates obtained from MCMC chains may move between rotationally equivalent solutions at each iteration, fixing the variance to one guarantees a unique solution for spatial factor loadings (Hogan and Tchernis, 2004). Note that fixing the variance does not fix the posterior distributions of the  $f_i$ 's. Spatial factor loadings ( $\lambda_k$ ) were each assigned positive half-normal prior distributions with means of zero and variances of

1,000 (Tzala and Best, 2008). This assumes that all spatial factor loadings are positive, as indicated by the positive pairwise correlations between all outcomes (Appendix B). Note that, while specifying alternative numerical values for the fixed variance of shared components does change the scale of the factor loadings, it does not influence the degree to which each type of crime and disorder is explained by the model components. As such, the type-specific factor loadings are interpreted relative to each other. For example, the influence of the shared spatial pattern ( $f_i$ ) on physical disorder is interpreted relative to the influence of the shared pattern on social disorder and is quantified by  $\lambda_1 / \lambda_2$ .

Type-specific temporal random effects terms ( $\gamma_{jk}$ ) were assigned ICAR prior distributions with type-specific conditional variances  $\delta_{\gamma_k}^2$  and temporal weights matrix  $Q$ .  $Q$  was defined such that year  $j$  had adjacent time periods of  $j + 1$  and  $j - 1$ , except for  $j = 1$  and  $j = 5$ , which each had only one adjacent time period (Thomas et al., 2004). This prior assumes that the time trends for each outcome were correlated between years (Richardson et al., 2006).

For the temporal shared component in Model 2–3, the logarithm of each factor loading was assigned a normal distribution with a mean of zero and a variance of 0.17 (i.e.,  $\log(\phi_k) \sim Normal(0, 0.17)$ ). This assumes that all  $\phi_k$ 's are positive and that the temporal factor loadings range between 0.2 and 5 with 95% probability (Knorr-Held and Best, 2001). A sum-to-zero constraint was imposed on the  $\log(\phi_k)$ 's (Held et al., 2005). This prior distribution is more informative than the prior specified for the spatial factor loadings but was required for convergence of  $\phi_k$ 's, likely because there was little temporal variability of crime and disorder (see Table 2.3; Appendix D; Figure 2.6). A less informative prior distribution of  $Normal(0, 0.5)$  was also tested for the  $\log(\phi_k)$ 's with nearly identical results to those presented in Table 2.3. The common temporally structured random effects terms ( $t_j$ ) were assigned ICAR prior distributions with temporal weights matrix  $Q$  and variances fixed to one to ensure model identifiability (Richardson et al., 2006; Tzala and Best, 2008). Like the spatial shared component, the magnitudes of the temporal factor loadings are interpreted relative to each other.

The standard deviations of type-specific random effects parameters ( $\delta_{s_k}$ ,  $\delta_{\gamma_k}$ , and  $\delta_{\theta_k}$ ) were assigned positive half-Gaussian prior distributions  $Normal_{+∞}(0, 10)$  (Gelman, 2006). To examine the sensitivity of the results to this prior, we tested  $Gamma(0.5, 0.0005)$  and  $Gamma(0.001, 0.001)$  distributions on the precisions of type-specific random effects and the results were similar to those presented here (Kelsall and Wakefield, 1999).

### **2.6.2. Model fitting, checking, and comparison**

All models were fit using the MCMC algorithm in WinBUGS v.1.4.3. Two MCMC chains were initiated at dispersed starting values and the convergence of model parameters was monitored via trace plots and Gelman-Rubin diagnostics. Convergence was reached at 50,000 iterations. Posterior summaries were obtained from an additional 50,000 iterations, where every tenth iteration was retained to reduce autocorrelation of posterior samples. The Monte Carlo errors of model parameters were less than five percent of the corresponding standard deviations, which indicates that the total number of iterations were sufficient to accurately estimate the posterior distributions of model parameters (Lunn et al., 2012).

Posterior predictive checks were used to test for potential discrepancies between the models and the observed data (Gelman et al., 1996). Ten thousand datasets ( $O^{rep}$ ) were generated from Models 2–1, 2–2, and 2–3, and the probability that  $O^{rep} \geq O$  was evaluated for four test statistics (T): the mean count, the standard deviation, the maximum count, and the skewness (Gilks et al., 1996). The probability  $\Pr(T(O^{rep}) \geq T(O))$  is referred to as the posterior predictive p-value. Posterior predictive p-values close to 0.5 indicate that the generated data are comparable to the observed data and p-values close to zero or one indicate a discrepancy between the model and the data. All models had posterior predictive p-values close to 0.5 for the four test statistics, showing that the generated data were consistent with the observed data (Appendix C).

Model fit was evaluated using the Deviance Information Criterion (DIC) and the Watanabe-Akaike Information Criterion (WAIC). The DIC and the WAIC both reward goodness of fit and penalize model complexity (Spiegelhalter et al., 2002; Gelman et al., 2014). While the DIC is the most common model fit criterion for Bayesian random effects models, it may under-penalize complex spatial models as shown by Plummer (2008). The WAIC has been proposed as an alternative measure of model fit that approximates leave-one-out cross-validation, a robust, albeit computationally expensive, method for assessing model fit (Stern and Cressie, 2000; Gelman et al., 2014). For the DIC, smaller values indicate better fitting models and differences of five or greater are evidence of substantial model improvement (Lunn et al., 2012). For the WAIC, smaller values also indicate better fitting models and the difference between expected log pointwise predictive densities (with standard errors) can help to identify which model exhibits better fit (see Table 2.2) (Vehtari et al., 2017).

## 2.7. Results

Table 2.2 compares Models 2–1, 2–2, and 2–3 using the DIC and the WAIC. Compared to separately modelling the spatiotemporal patterns of each type of crime and disorder in Model 2–1, adding a spatial shared component in Model 2–2 resulted in improved model fit. Decreases in the DIC and the WAIC from Model 2–1 to Model 2–2 were attributable to both improved goodness of fit (smaller  $\overline{D}$  and  $\text{lpd}_{\text{WAIC}}$ ) and fewer effective parameters (smaller  $p_D$  and  $p_{\text{WAIC}}$ ). Adding a temporal shared component in Model 2–3 also led to smaller DIC and WAIC values, with improvements in goodness of fit at the expense of slightly greater model complexity. As per the DIC, neither Model 2–2 or Model 2–3 was favored as values were within five. As per the WAIC, the difference in the expected log pointwise predictive densities between Models 2–2 and 2–3 was 3.3 with a standard error of 2.0 in favor of Model 2–3. Focusing on the parameter estimates from Models 2–2 and 2–3, the posterior distributions of the parameters that explained the largest proportions of variability in both models were nearly identical (Figure 2.6; Appendix D), however the type-specific temporal components for

all outcomes in Model 2–2 were greater than one during the first two years and less than one during the final two years. This qualitatively supports the common time trend included in Model 2–3.

Therefore, Model 2–3 was chosen as the preferred model.

**Table 2.2 DIC and WAIC results for the three multivariate spatiotemporal models.**

Model	$\bar{D}$	pD	DIC <sup>a</sup>	lpd <sub>WAIC</sub>	p <sub>WAIC</sub>	WAIC <sup>b</sup>
2–1	44,263	4,265	48,528	-20,864	3,463	48,654
2–2	44,124	3,838	47,962	-20,919	3,085	48,008
2–3	44,117	3,842	47,959	-20,915	3,086	48,002

<sup>a</sup> DIC =  $\bar{D}$  + pD, where  $\bar{D}$  is the posterior mean of the deviance and pD is the effective number of parameters (Spiegelhalter et al., 2002).

<sup>b</sup> WAIC = -2(elpd<sub>WAIC</sub>), where elpd<sub>WAIC</sub> is the expected log pointwise predictive density. elpd<sub>WAIC</sub> = lpd<sub>WAIC</sub> - p<sub>WAIC</sub>, where lpd<sub>WAIC</sub> is the log posterior predictive density and p<sub>WAIC</sub> is the effective number of parameters (Gelman et al., 2014; Vehtari et al., 2017).

Table 2.3 shows the posterior medians and 95% credible intervals (95% CI) of the type-specific intercepts, the regression coefficients, the factor loadings, and the empirical variances of random effects terms from Model 2–3. The 95% CI is the interval that contains the true value of a parameter with 95% probability. Regression coefficients are shown as relative risks ( $\exp(\beta_{nk})$ ) where values greater than one indicate positive associations between explanatory variables and crime/disorder. Residential population, residential mobility, and the central business district were found to be positively associated with all types of crime and disorder at 95% CI. This supports collective efficacy theory, which posits that crime and disorder are most frequent in areas where high residential mobility challenges the formation of social ties amongst residents and contributes to low informal social control (Sampson and Groves, 1989; Sampson et al., 1997; Boggess and Maskaly, 2014).

These results also support past routine activity research showing that crime and disorder disproportionately occur in downtown areas where offenders and potential targets converge during employment and leisure activities, and where the night-time economy is concentrated (Nelson et al., 2001).

**Table 2.3 Posterior medians and 95% credible intervals of the intercept, regression coefficients, factor loadings, and empirical variances of random effects terms from Model 2–3.**

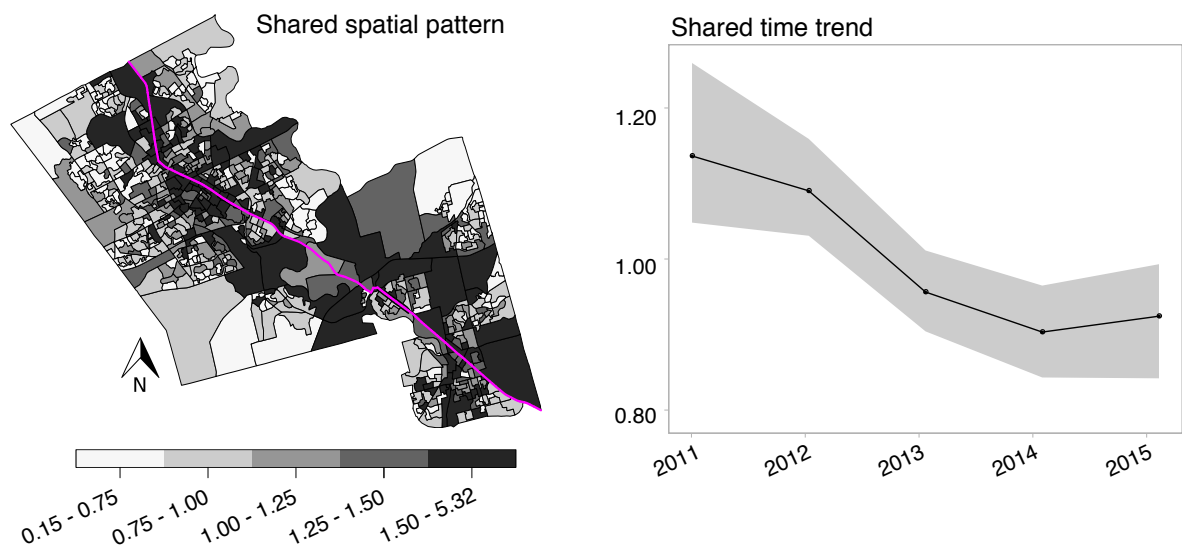
	Physical disorder	Social disorder	Property crime	Violent crime
Intercept ( $\exp(\alpha_k)$ )	1.67 (1.61, 1.73)	1.30 (1.24, 1.35)	6.92 (6.77, 7.07)	0.78 (0.74, 0.82)
Residential population	1.33 (1.24, 1.43)	1.39 (1.26, 1.52)	1.34 (1.25, 1.44)	1.35 (1.23, 1.49)
Residential mobility	1.24 (1.13, 1.35)	1.27 (1.13, 1.42)	1.21 (1.10, 1.33)	1.26 (1.11, 1.41)
Low-income households	0.95 (0.88, 1.04)	1.01 (0.90, 1.12)	0.93 (0.85, 1.02)	1.02 (0.91, 1.15)
Ethnic heterogeneity	0.99 (0.92, 1.09)	1.00 (0.90, 1.12)	1.04 (0.96, 1.15)	0.97 (0.87, 1.10)
Central business district	1.65 (1.01, 2.68)	2.10 (1.14, 3.86)	1.63 (0.96, 2.65)	1.81 (0.97, 3.39)
Spatial factor loading	1.90 (1.77, 2.03)	2.60 (2.45, 2.77)	1.93 (1.80, 2.07)	2.57 (2.40, 2.75)
Temporal factor loading	1.18 (0.66, 1.98)	0.78 (0.46, 1.53)	1.08 (0.60, 1.80)	1.00 (0.60, 1.68)

Empirical variances of random effects terms				
Spatial shared component: $\lambda_k \cdot f_i$	0.84 (0.74, 0.95)	1.58 (1.43, 1.75)	0.87 (0.77, 0.99)	1.54 (1.38, 1.74)
Temporal shared component: $\phi_k \cdot t_j$	0.02 (0, 0.05)	0.01 (0, 0.04)	0.006 (0, 0.05)	0.01 (0, 0.05)
Type-specific spatial: $s_{ik}$	0.13 (0.09, 0.17)	0.03 (0, 0.10)	0.23 (0.20, 0.27)	0.13 (0.08, 0.19)
Type-specific temporal: $\gamma_{jk}$	0.004 (0, 0.03)	0.001 (0, 0.02)	0.002 (0, 0.02)	0.001 (0, 0.02)
Type-specific space-time: $\theta_{ijk}$	0.13 (0.10, 0.16)	0.07 (0.05, 0.09)	0.09 (0.07, 0.11)	0.08 (0.06, 0.12)

Factor loadings ( $\lambda_k$  and  $\phi_k$ ) quantify the relative associations between each type of crime and disorder and the shared spatial pattern ( $f_i$ ) and the shared time trend ( $t_j$ ) (Table 2.3). The magnitudes of factor loadings are interpreted relative to each other because the variances of  $f_i$  and  $t_j$  were fixed to one (Held et al., 2005). The spatial factor loadings for social disorder and violent crime were significantly greater than the loadings for physical disorder and property crime at 95% CI. Compared to physical disorder, which had the smallest spatial factor loading, the shared spatial pattern had a 1.37 times greater association with social disorder ( $2.60 / 1.90 = 1.37$ ), a 1.35 times greater association with violent crime ( $2.57 / 1.90 = 1.35$ ), and a similar magnitude of association with property crime ( $1.93 / 1.90 = 1.02$ ). Temporal factor loadings had relatively greater positive associations with physical disorder, property crime, and violent crime than with social disorder, however all temporal factor loadings had overlapping posterior distributions at 95% CI.



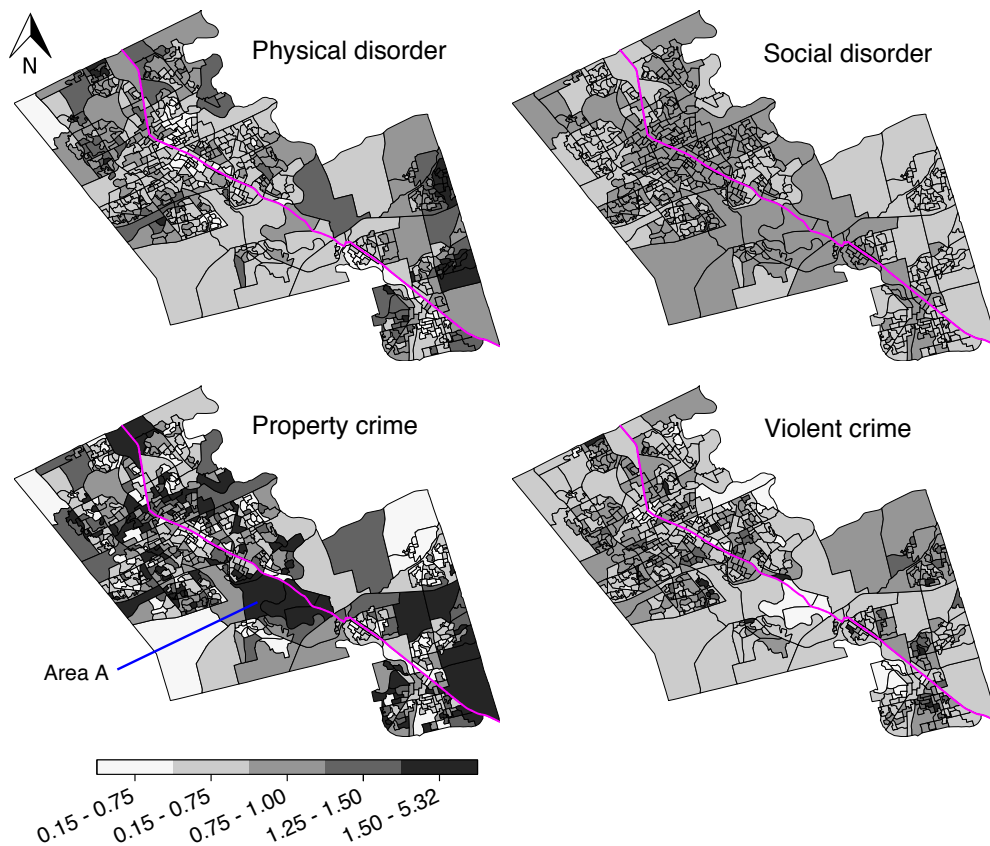
The shared spatial pattern ( $\exp(f_i)$ ) and the shared time trend ( $\exp(t_j)$ ) from Model 2–3 are visualized in Figure 2.3. The relative risk of the shared spatial pattern was highest along the central commercial corridor and lowest in areas west of the central commercial corridor and in areas around the periphery of the study region. This aligns with the visual similarities of the crime and disorder counts mapped in Figure 2.1. The shared time trend common to all outcomes decreased from 2011 to 2014, which is generally representative of the trend shown by the observed crime and disorder counts (see Figure 2.2). The increase in the shared time trend from 2014 to 2015 is likely attributable to property crime as it was the most frequent crime/disorder type analyzed (see Table 2.1).



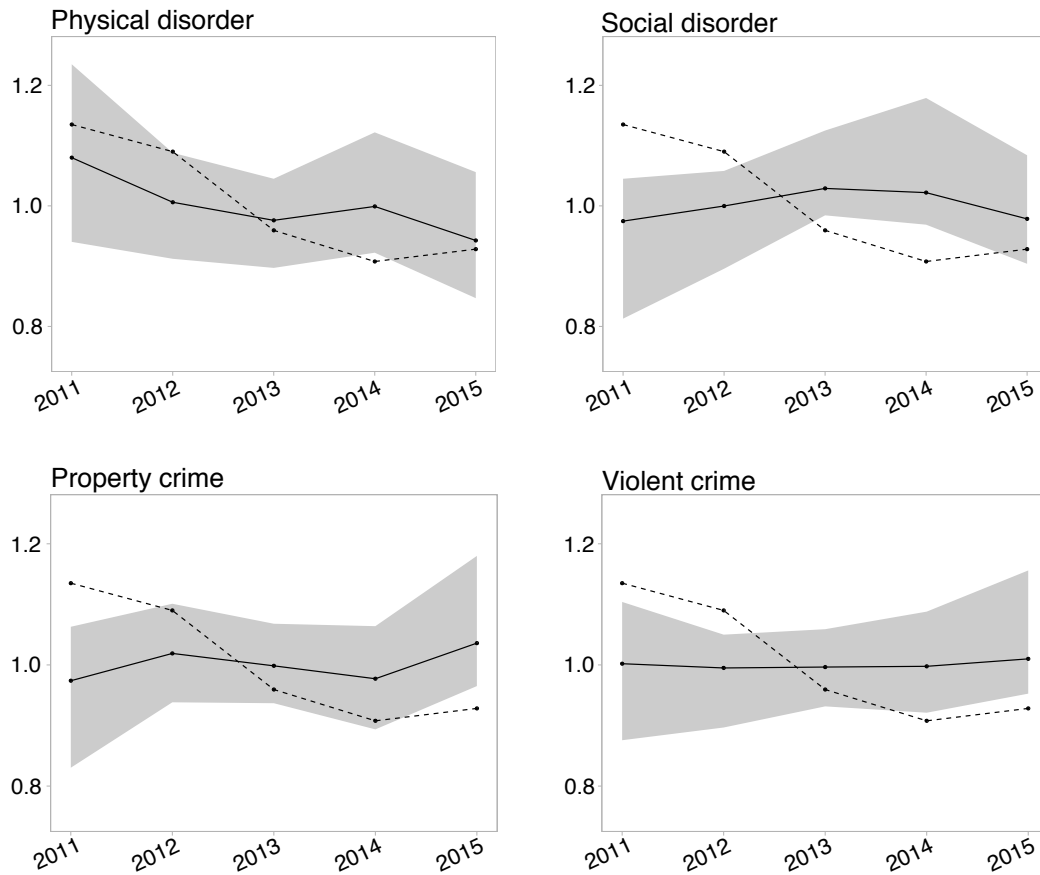
**Figure 2.3. The shared spatial pattern and the shared time trend common to all types of crime and disorder. The 95% CI for the shared time trend is shaded grey.**

Type-specific spatial patterns ( $\exp(s_{ik})$ ) and time trends ( $\exp(\gamma_{jk})$ ) are visualized in Figure 2.4 and Figure 2.5, respectively. Property crime had the largest empirical variance for the type-specific spatial component (= 0.23) and exhibited the most heterogeneous spatial pattern, with areas of high risk located in the south and southeast of the study region (see Table 2.3). Social disorder had the smallest empirical variance for the type-specific spatial component (= 0.03) and exhibited a relatively uniform pattern throughout the study region. Physical disorder and violent crime had similar

empirical variances for the type-specific spatial components but exhibited distinct patterns; areas with high type-specific risk of physical disorder were found in large clusters in the northwest and southeast of the study region, and areas with high type-specific risk of violent crime were located in smaller clusters near the central commercial corridor (Figure 2.4). The type-specific temporal components had the smallest empirical variances of all model parameters and the posterior distributions of  $\exp(\gamma_{jk})$  were not unambiguously different from  $\exp(t_j)$  at 95% CI (Figure 2.5). This suggests that the residual type-specific time trends were indistinguishable from the shared time trend.



**Figure 2.4. Type-specific spatial patterns of physical disorder, social disorder, property crime, and violent crime.**

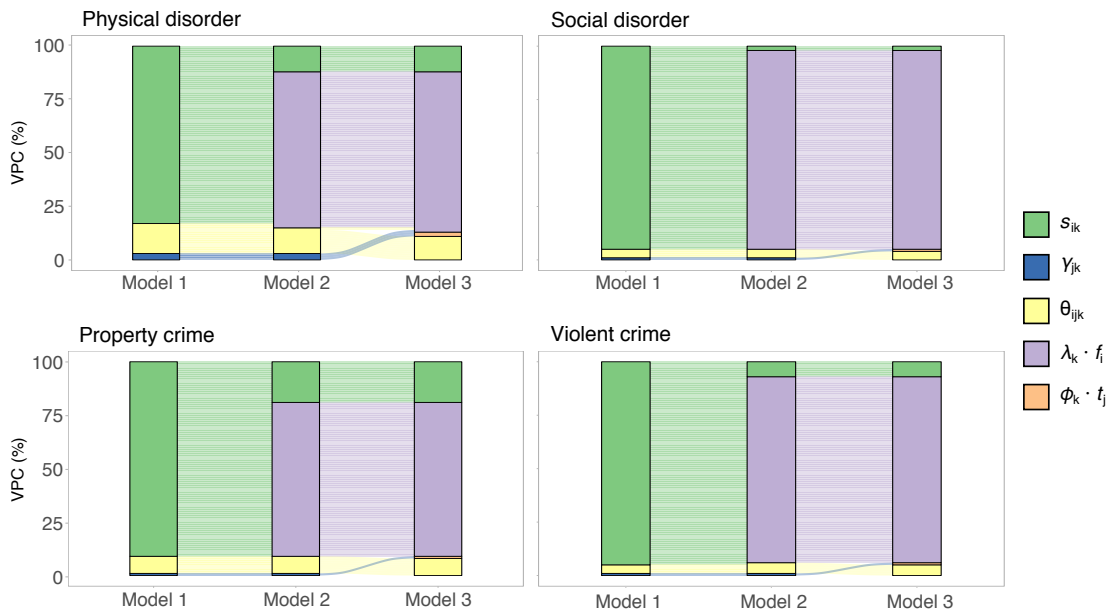


**Figure 2.5. Type-specific time trends of physical disorder, social disorder, property crime, and violent crime. The 95% CIs for the type-specific time trends are shaded grey. The shared time trend is shown as a dashed line.**

Variance partition coefficients (VPC) quantify the proportion of residual variability explained by shared and type-specific components for each crime and disorder type<sup>3</sup>. VPCs are visualized in Figure 2.6 (see Appendix D for posterior medians and uncertainty intervals). In Model 2–1, the type-specific spatial components had the largest VPCs for all types of crime and disorder, however almost all of this variability was captured by the spatial shared component in Models 2–2 and 2–3. Indeed, the spatial shared component had the largest VPCs for all outcomes, accounting for approximately

<sup>3</sup> For example, the VPC for the type-specific spatial component for physical disorder in Model 1 is the empirical variance of  $s_{i1}$  divided by the sum of the empirical variances of  $s_{i1}$ ,  $\gamma_{j1}$ , and  $\theta_{ij1}$ .

93% of the residual variability of social disorder, 87% of violent crime, 75% of physical disorder, and 72% of property crime. Like the spatial shared component, the temporal shared component added in Model 2–3 captured almost all of the variability explained by the type-specific temporal components in Models 2–1 and 2–2 and, consequently, the type-specific temporal components had the smallest VPCs for all outcomes.



**Figure 2.6. Variance partition coefficients for Models 2–1, 2–2, and 2–3.**

## 2.8. Discussion

This article has applied a Bayesian multivariate modelling approach to analyze the spatiotemporal patterning of physical disorder, social disorder, property crime, and violent crime over five years at the small-area scale. Three models with different assumptions regarding the spatial and temporal correlation structures between the four outcomes were compared. The best-fitting model accounted for five covariates operationalizing population size, socioeconomic contexts, and the central business districts, and partitioned the residuals of each outcome into one spatial shared component, one temporal shared component, and four type-specific spatial, temporal, and space-time components. For all types of crime and disorder, the largest proportions of residual variability were explained by the

spatial shared component and the smallest proportions of residual variability were explained by the type-specific temporal components.

Multivariate spatiotemporal models provide a framework for analyzing two or more correlated dependent variables that each exhibit spatial and temporal structure. In this research, the correlation structures between physical disorder, social disorder, property crime, and violent crime were estimated via one spatial shared component and one temporal shared component, which allow for each type of crime and disorder to be explained by a set of spatial random effects and a set of temporal random effects common to all outcomes (Knorr-Held and Best, 2001; Hogan and Tchernis, 2004). This research shows that adding shared components to capture the spatial pattern and time trend shared amongst all types of crime and disorder substantially improves model fit compared to analyses that assume that the spatiotemporal patterns of physical disorder, social disorder, property crime, and violent crime are not correlated with each other. Importantly, shared components are enabled by multivariate modelling of two or more dependent variables and are therefore overlooked when only one outcome is analyzed. For example, cluster detection techniques, which are the most common quantitative methods used to compare the patterns of multiple crime types, typically analyze a single variable, do not accommodate covariates that may be associated with crime and disorder, and rely on researcher interpretation of hotspot locations and durations to infer the correlations between crime and disorder types (Leitner and Helbich, 2011; Haberman, 2017).

Conceptually, shared components represent latent risk factors that are simultaneously associated with two or more dependent variables (Held et al., 2005; MacNab, 2010). For physical disorder, social disorder, property crime, and violent crime, shared components are justified by broken windows and collective efficacy theories, both of which contend that crime and disorder are correlated within areas, between areas, and between time periods because they manifest from the same underlying social and behavioural processes (see Section 3). The results of this study show that, for all crime and disorder types, the spatial and temporal shared components explain larger

proportions of residual variability than the corresponding type-specific parameters (Figure 2.6). This suggests that the shared spatial pattern and shared time trend are more important for understanding when and where crime and disorder occur than the separable type-specific patterns despite being overlooked in past research.

### **2.8.1. Multivariate modeling and collective efficacy theory**

Enabled by multivariate spatiotemporal modelling with shared components, this research provides novel insights for both ecological crime theories and crime prevention policy. Focusing on theoretical inference, the regression coefficients and spatial factor loadings provide support for collective efficacy theory. In particular, residential mobility was found to be positively associated with all types of crime and disorder, and all spatial factor loadings were found to be unambiguously greater than zero (Table 2.3). This aligns with collective efficacy research observing that neighborhoods with high residential mobility also have high levels of crime and disorder (Sampson and Raudenbush, 1999), but extends past studies by showing that, even after controlling for the structural characteristics operationalizing collective efficacy, all outcomes were positively associated with a common spatially structured latent risk factor (Table 2.3). This common risk factor had a significantly greater influence on social disorder and violent crime than on physical disorder and property crime, as indicated by the spatial factor loadings. In this context, the spatial shared component may capture dimensions of collective efficacy not measured via residential mobility, low-income households, and ethnic heterogeneity, for example peer group supervision or the degree to which residents will intervene in criminal behaviour (Sampson and Groves, 1989; Sampson et al., 1997).

Differentiating between the shared and type-specific components, physical disorder and property crime had relatively more heterogeneous type-specific spatial patterns and relatively larger VPCs for the type-specific space-time components than did social disorder and violent crime (Figure 2.4; Figure 2.6). One explanation for the greater divergence of physical disorder and property crime

from the shared spatial pattern and the shared time trend is that, whereas social disorder and violent crime were predominately influenced by collective efficacy, as measured via the explanatory variables and the shared components, physical disorder and property crime were explained by collective efficacy as well as features of the built environment that were not included in this analysis (Sampson et al., 1997; Sampson and Raudenbush, 1999; Yang 2010). As highlighted by routine activity theory, physical features of the built environment, such as retail stores and infrastructure, are necessary for property crime and physical disorder incidents to occur. For example, the areas located in the southwest of the study region with high type-specific spatial risk of property crime (Area A in Figure 2.4), but low type-specific spatial risk of all other outcomes, are near to a large shopping mall that provides many opportunities for property crimes but relatively fewer opportunities for incidents of violent crime or disorder.

### **2.8.2. Space-time hotspots, the broken windows theory, and policy applications**

In addition to furthering the analysis of multiple correlated small-area outcomes and advancing theoretical inference, this multivariate modelling approach provides information regarding if, and how, areas with high levels of disorder transition to high levels of crime as proposed by broken windows theory. To date, little research has examined which types of disorder precede which types of crime after controlling for the effects of collective efficacy (i.e., the explanatory variables and the shared components). Hotspots of the type-specific space-time random effects terms were identified via the posterior probability  $\Pr(\exp(\theta_{ijk}) > 1 \mid \text{data}) > 0.8$  (Richardson et al., 2004) and the number of disorder hotspots at time  $j$  that occurred one year prior to at least one crime hotspot in the same area or adjacent areas at time  $j + 1$  were counted. Areal adjacency was determined via spatial weights matrix  $W$  (see Section 2.5.1). Boggess and Maskaly (2014) suggest that one year is an appropriate time frame for areas with high disorder to transition to high crime. Hotspot transitions are shown in Table 2.4.

In this case study, transitions from hotspots of social disorder or physical disorder to hotspots of property crime or violent crime were relatively infrequent (total of 297 over five years) compared to the number of small-areas analyzed (total of 3,275 over five years). The most common type of ‘broken windows’ transition was from hotspots of physical disorder to hotspots of property crime, accounting for nearly half of all hotspot transitions. Relative to the total number of disorder hotspots, however, the most prevalent type of transition was from social disorder to property crime (64%). Substantially fewer social disorder or physical disorder hotspots transitioned to violent crime hotspots in the following year (Table 2.4).

**Table 2.4. Areas that transition from disorder hotspots in year  $j$  to crime hotspots in year  $j + 1$ . The percentage of transition areas relative to the total number of disorder hotspots is shown in parentheses.**

	Violent crime	Property crime
Social disorder	39 (34.8%)	72 (64.3%)
Physical disorder	48 (21.7%)	138 (60.1%)

Applied to policy, ‘broken windows’ transitions between hotspots of disorder to hotspots of crime suggest that law enforcement should scan for high levels of physical and social disorder and, in the next year, deploy geographically-focused crime prevention programs designed specifically to prevent property crime. Yet, because ‘broken windows’ transitions are relatively uncommon, and because the type-specific space-time components explain a smaller proportion of the overall variability than the spatial shared component for all four outcome types (Figure 2.6), it may be more effective for law enforcement resources and place-based crime prevention policies to focus on centrally located neighborhoods with high residential mobility and with high risk due to the shared spatial pattern. That is, rather than implement policing strategies designed for a single crime type or deploy resources based on anticipated transitions from disorder to crime, programs and policies that target areas with consistently high risk due to the spatial shared component, and that attempt to



increase informal social control and social cohesion, may have the largest impact on all types of crime and disorder (Sampson and Raudenbush, 2004; Haberman, 2017).

### **2.8.3. Limitations and future research**

One limitation of this research is that crime and disorder data were obtained from a reported incident dataset and were retrieved from a single law enforcement agency. While reported incident data are commonly used in past research (Skogan, 1990; Braga and Bond, 2008; Yang, 2010), it is possible that the correlations between outcomes reflect, in part, the existing distribution of police resources or data misclassification between related incidents, such as physical disorder and property crime (Nelson et al., 2001). A second limitation is that the spatial shared component, which specifies an ICAR prior distribution for the common spatially structured random effects terms, assumes that the shared pattern exhibits local spatial autocorrelation and that the shared pattern, as well as the relative influence of the shared pattern on all outcomes, is stable over time (Knorr-Held and Best, 2001). However, it is possible that the correlation structures between outcomes can be similar amongst groupings of non-adjacent areas, and that the shared pattern and the factor loadings can change over time. One method to explore in future research is profile regression modelling, which can identify groups of adjacent and non-adjacent small-areas with similar relative risks of multiple outcomes (Liverani et al., 2016). Studies should also explore the methodological and practical implications of allowing the correlation structure between outcomes to change over space and/or time, perhaps by estimating space- or time-varying factor loadings. Third, we include three covariates to operationalize collective efficacy at the small-area scale, however recent studies have shown that the relationships between neighborhood structural characteristics and social processes are contextual and interact with broader patterns of diversity and segregation (Sturgis et al., 2014; Laurence, 2017). Future studies may look to apply this multivariate modelling approach at multiple spatial scales, exploring if regression coefficients and

shared components are consistent across scales and examining how shared components change after controlling for socio-spatial processes operating at larger areal units.

Future research should also investigate how shared and type-specific patterns of crime and disorder evolve over shorter and longer time periods. For shorter temporal units, such as months, this method would be helpful in evaluating the effects of policing tactics on all, or only a subset, of crime outcomes. For longer time periods, such as decades, multivariate spatiotemporal modelling can be used to explore how processes of urban change lead to increases or decreases in multiple crime and disorder types. If analyzing counts of specific crime types, future research should consider different operationalizations of population at risk. For crime types such as residential burglary, the number of dwellings can be incorporated into Poisson models as an offset (e.g., Li et al., 2014), however for more ambiguous crime types such as violent and property crimes, supplementing the residential population with quantitative estimates of the daytime population and the prevalence of night-time activities may be informative.

## **Chapter 3: Time-varying relationships between land use and crime: A spatiotemporal analysis of small-area seasonal property crime trends<sup>4</sup>**

### **3.1. Summary**

Neighbourhood land use composition influences the geographical patterns of property crime. Few studies, however, have investigated if, and how, the relationships between land use and crime change over time. This research applies a Bayesian spatiotemporal modeling approach to analyze twelve seasons of property crime at the small-area scale. Time-varying regression coefficients estimate the seasonally-varying relationships between land use and crime and distinguish both time-constant and season-specific effects. Seasonal property crime trends are commonly hypothesized to be associated with fluctuating routine activity patterns around specific land uses, but past studies do not quantify the time-varying effects of neighbourhood characteristics on small-area crime risk. Accounting for sociodemographic contexts, results show that parks are more positively associated with property crime during spring and summer seasons, and that eating and drinking establishments are more positively associated with property crime during autumn and winter seasons. Land use was found to have a greater impact on spatial, rather than spatiotemporal, crime patterns. Proposed explanations for the results focus on seasonal activity patterns and corresponding spatiotemporal interactions with the built environment. The theoretical and analytical implications of this modeling approach are discussed. This research advances past cross-sectional spatial analyses of crime by identifying the built environment characteristics that shape both where and when crime events occur.

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### 3.2. Introduction

Geographical patterns of property crime are influenced by neighbourhood-scale built environment characteristics (Ceccato et al., 2002; Matthews et al., 2010). Local land use composition shapes the situational conditions necessary for crime offences to occur and is often interpreted through routine activity theory, which hypothesizes that crime offenses result from the convergence of motivated offenders, suitable targets, and a lack of capable guardianship in space and time (Cohen and Felson, 1979; Andresen, 2007). Past research has found, for example, that the spatial distribution of property crime is positively associated with non-residential land uses such as commercial uses and public transit stations (Kinney et al., 2008; LaGrange, 1999; Matthews et al., 2010; Weisburd et al., 2012; Wilcox et al., 2004). However, despite routine activity theory proposing a spatiotemporal relationship between land use and crime, or that land use simultaneously influences both where and when crime offences occur, past small-area research has generally applied cross-sectional analytical methods and has not investigated if, and how, the relationships between land use and crime change over time.

Seasonal crime trends are one of the most robust temporal patterns of crime and are typically observed to be highest during the summer and lowest during the winter (Anderson, 1987; Andresen and Malleson, 2013; Hipp et al., 2004). Proposed routine activity theory explanations focus on how the uses and functions of urban space change over time, and in particular, how discretionary activities vary around specific land use types (McDowall et al., 2012). Discretionary routine activities are pursued by choice and vary in both location and temporal frequency. Obligatory routine activities, in contrast, are consistent in location and frequency (LeBeau, 1994; Tompson and Bowers, 2015). The difference between high property crime rates during the summer and low rates during the winter, for example, has been attributed to summertime increases in discretionary leisure activities, such as public events and festivals located around parks and open spaces, and around land uses that offer shopping and dining activities (Cohn and Rotton, 2000; Hipp et al., 2004; Sorg and Taylor, 2011).

Seasonal crime research has often applied time-series methods to analyze longitudinal data for one or more large geographical areas, such as a country or a collection of cities (Breetzke and Cohn, 2012). While these analyses identify generalizable city-level crime trends and associated climatic characteristics (Linning 2016; 2017), they overlook intra-urban heterogeneity in crime and do not recognize the place-based relationships between crime and the built environment (di Bella et al., 2015; Gorman et al., 2013). In routine activity theory, it is local land use composition that is thought to shape the spatiotemporal distribution of behavioural activity patterns, the availability of property crime targets (i.e., physical goods that can be damaged or stolen), and the spatiotemporal frequency of convergences between potential offenders and targets (Ceccato et al., 2002; Groff et al., 2014; Groff and Lockwood, 2014). Research exploring small-area crime trends has suggested that land use does influence local crime trends, but inferences and policy recommendations are based on descriptive methods rather than statistical analyses that quantify the relationships between crime and land use over time while accounting for the effects of social, economic, and demographic contexts (Andresen and Malleson, 2013; Brunson et al., 2009).

This research investigates the time-varying relationships between land use and property crime at the small-area scale. The case study location for this research is the Region of Waterloo, Canada, for twelve seasons from Spring 2011 to Winter 2013-2014. A set of Bayesian spatiotemporal regression models with time-varying coefficients and random effects are applied. Briefly, Bayesian models combine observed data (i.e., observed crime counts and risk factors) and prior knowledge about the study region (i.e., spatial adjacency between small-areas and temporal adjacency between seasons) to estimate full posterior probability distributions for all model parameters. Random effects capture residual spatial and temporal autocorrelation that may bias model results if unaccounted for. Time-varying coefficients are composed of time-constant and time-changing components and estimate the underlying relative risk of land use and season-specific departures, respectively. The

structure of time-varying coefficients parallel the distinction between obligatory (time-constant) and discretionary (time-varying) routine activities.

This chapter begins with a review of past research exploring seasonal crime trends and the spatiotemporal mechanisms through which the built environment is hypothesized to influence local crime patterns. Next, the Bayesian spatiotemporal regression modeling approach is outlined, the seasonally-varying relationships between land use and crime are visualized, and explanations for the observed results are proposed. The theoretical, analytical, and policy implications of this modeling approach are discussed and, in conclusion, the limitations of this study and topics for future research are highlighted.

### **3.3. Literature review**

Contemporary research has observed that property crime typically exhibits a recurring trend that is highest during summer seasons and lowest during winter seasons (Breetzke and Cohn, 2012; Hipp et al., 2004). In general, past research has analyzed longitudinal crime data for one large geographical area. For example, Anderson (1987) identify significant differences between seasonal crime rates using analysis of variance methods and find that, in the United States, burglary, theft, and motor vehicle theft were highest between April and September. A similar quantitative approach found that pickpocketing was highest during the summer in Hong Kong (Yan, 2004). Linning and colleagues (2016; 2017) apply Poisson and negative binomial regressions to analyze the relationship between climatic characteristics and property crime, observing that city-scale property crime rates were positively associated with temperature and negatively associated with snowfall.

Time series methods have also been applied to longitudinal crime data for one or many large geographical areas. For example, Cohn and Rotton (2000) identify a positive and statistically significant association between burglary, robbery, and theft rates and the months of June, July, and August, for the city of Minneapolis, Minnesota. Hipp et al. (2004) and McDowall et al. (2012)

analyzed longitudinal crime data for over eight thousand police unit areas and eighty-eight cities in the United States, respectively, and found that property crimes were highest in summer months after accounting for city temperatures. Notably, Hipp et al. (2004) also identified a positive relationship between seasonal property crime oscillations and eating and drinking establishments, but do not consider how this land use type influences property crime trends at the small-area scale. Both analysis of variance methods and time series methods do not provide insight into how local land use influences local seasonal crime trends, as hypothesized by routine activity theory.

### **3.3.1. Seasonal routine activities and land use**

Historically, seasonal crime trends have been interpreted through routine activity theory and/or temperature-aggression theory (McDowall et al., 2012). Temperature-aggression theory posits that high temperatures lead to aggressive behaviour and high violent crime (Cohn, 1990). Routine activity theory, in contrast, hypothesizes that seasonal changes in activity patterns shape the spatiotemporal distribution of all crime types (Cohen and Felson, 1979; Field, 1992). Compared to temperature-aggression theory, routine activity theory offers a place-based and spatiotemporal explanation for property crime, emphasizes how the built environment shapes crime opportunities, and provides a framework for interpreting why small-areas with specific land use types may exhibit high crime during any seasonal time period (Hipp et al., 2004; McDowall et al., 2012).

Routine activities are defined as “recurrent and prevalent activities which provide for basic population and individual needs (Cohen and Felson, 1979: 593).” In a spatiotemporal context, routine activities can be distinguished as obligatory or discretionary. Obligatory activities are consistent throughout the year, both in geographical location and temporal frequency, and include household activities located in residential neighbourhoods, occupational activities located in employment areas, and commuting between residential and employment areas. Discretionary activities, on the other hand, are pursued by choice and exhibit fluctuating spatiotemporal patterns (Tompson and Bowers,

2015). Generally, research has suggested that discretionary activities are concentrated in indoor locations and in residential areas during autumn and winter seasons, but increasingly occur in outdoor locations and in non-residential areas with public space during the spring and summer (Field, 1992).

Proposed routine activity theory explanations for seasonal property crime trends focus on spatiotemporal variations in the convergence of offenders and targets or on spatiotemporal variations in the presence of capable guardianship. Focusing on offender and target convergence, past research has suggested that leisure activities occur more frequently during the summer, and that these activities occur at specific non-residential land uses (Hipp et al., 2004; Sorg and Taylor, 2011). For example, increases in shopping, dining, and tourism during summer months are geographically concentrated at commercial and retail stores, eating and drinking establishments, and public transit stations (Hipp et al., 2004; Sorg and Taylor, 2011; Carbone-Lopez and Lauritsen, 2013). Furthermore, outdoor events in the summer bring together large numbers of people during festivals and civic events in public spaces such as parks and central business districts (Andresen and Malleson, 2013; Cohn and Rotton, 2000; Linning, 2015). Some proportion of people participating in these leisure activities or outdoor events during the summer may engage in criminal behaviour, whether motivated or opportunistic, and lead to increased property crime rates both for specific small-areas and for the study region.

Focusing on the presence of capable guardianship, it has been hypothesized that as discretionary activities shift from residential to non-residential areas in the summer, there are fewer capable guardians in residential neighbourhoods. Consequently, this may increase the attractiveness of property crime targets and the likelihood that criminal opportunities are acted upon (Landau and Fridman, 1993; Linning, 2015). This increase in property crime risk may be amplified by higher numbers of vacant residences due to vacations (Cohn and Rotton, 2000). As discretionary activities shift to residential areas during autumn and winter seasons, however, there is thought to be decreasing frequencies of offender and target convergences in both residential and non-residential areas, leading



to increasing levels of guardianship decreasing levels of property crime across the study region (Breetzke and Cohn, 2012).

### **3.3.2. Local seasonal crime trends and land use**

While it appears that the land use characteristics of high crime areas are relatively consistent between years (Weisburd et al., 2012: 128), past research at the small-area scale contends that the relationships between land use and crime fluctuate between seasons. Andresen and Malleson (2013) compare monthly crime data for census tracts in Vancouver, Canada, and observe that high property crime rates in the summer are located in the central business district or in areas characterized by parks and commercial land uses. Comparing seasonal property crime trends between Canadian cities with a temperate climate (Ottawa) and a coastal climate (Vancouver), Linning (2015) observes that streets with increasing property crime counts in the summer are located in central business districts with entertainment and commercial land uses. Brunsdon et al. (2009) suggest that disorder incidents increase in small-areas with outdoor public spaces during warm temperatures in an urban area in the United Kingdom.

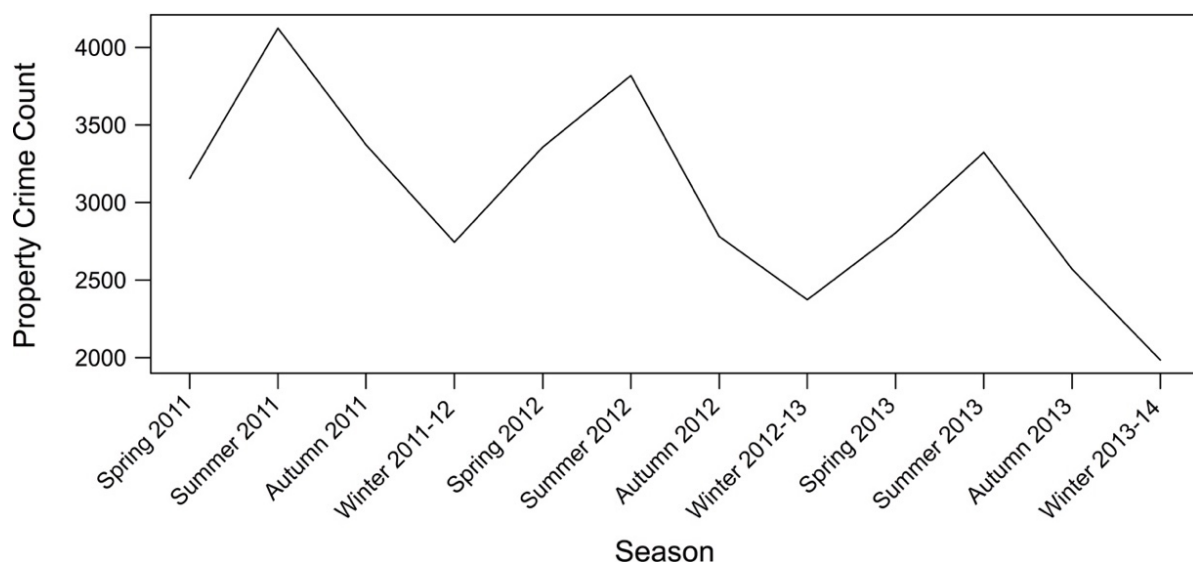
Methodologically, small-area studies have been descriptive and have not quantified how the relationships between land use and crime vary over time. Andresen and Malleson (2013) and Linning (2015) compare spatial crime patterns between two seasons, but do not explore how seasonal variations in crime are associated with neighbourhood characteristics. Brunsdon et al. (2009) interpolate spatial crime patterns for each time period and visually compare maps to infer how local changes in disorder vary around built environment features. Sorg and Taylor (2011) apply a cross-sectional regression model to analyze the relationship between street robbery and temperature for three years at the census tract scale, operationalizing month as a binary variable, and observe that small-area commercial and public transit land uses amplify the positive effect of temperature. The

modeling approach used by Sorg and Taylor (2011) does not account for residual temporal structure of crime trends nor does it consider how the relationships between land use and crime vary over time.

### **3.4. Study region and data**

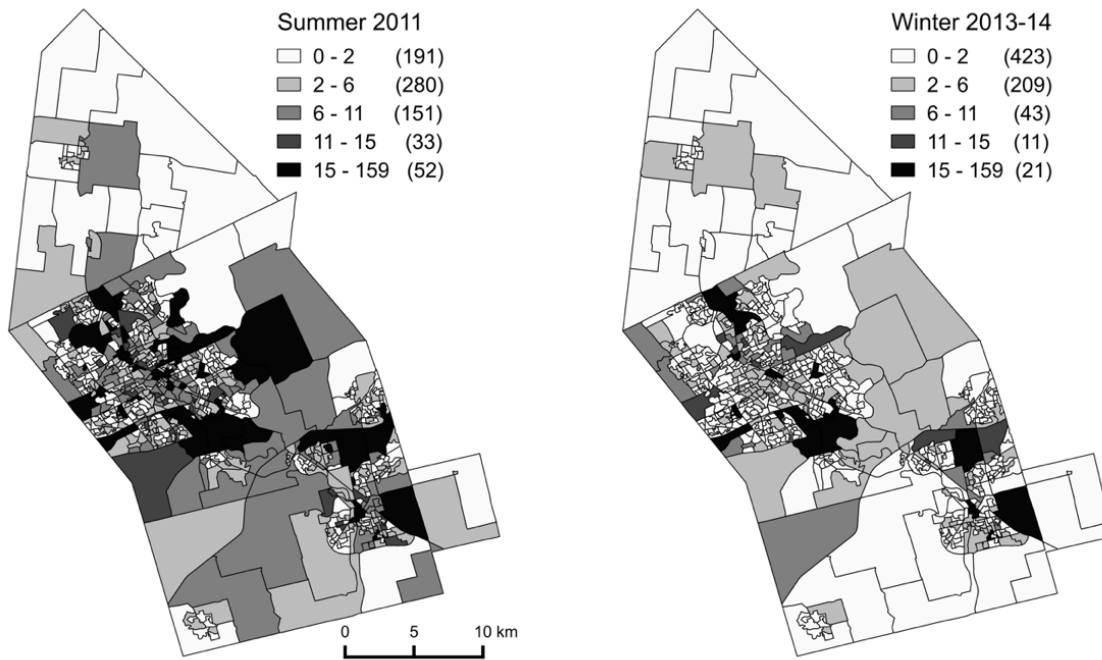
The Regional Municipality of Waterloo is located in Ontario, Canada, and is composed of the cities of Waterloo, Kitchener, and Cambridge, and four townships. The geographic unit of analysis was the dissemination area (DA). DAs are the smallest statistical unit that cover the entirety of Canada and have residential populations between 400 and 700. In the study region, there were 707 DAs with an average area of 1.17 km<sup>2</sup>. DAs were chosen as the geographic unit of analysis because they provide a common unit for integrating crime data with small-area sociodemographic and built environment data, and because they are small enough to reflect land use heterogeneity within the study region. Note that the study region used in this Chapter is the Kitchener–Cambridge–Waterloo Census Metropolitan Area as defined by Statistics Canada. This is different from the study regions used in Chapters 2 and 4, which were the municipal boundaries of the cities of Kitchener, Cambridge, and Waterloo (see Appendix A).

Reported property crime data was obtained from Waterloo Regional Police Services for twelve seasons from Spring 2011 to Winter 2013-14. Reported property crime incidents were aggregated from street intersections to DAs using a point-in-polygon method. Property crimes were the sum of break and enters, thefts under \$5,000, thefts over \$5,000, motor vehicle thefts, property damage, and graffiti incidents (Cohn and Rotton, 2000; Matthews et al., 2010). Figure 3.1 shows seasonal property crime trend for the study region. Consistent with past research, property crime was highest in summer seasons and lowest in winter seasons (Anderson, 1987; Hipp et al., 2004).



**Figure 3.1. Seasonal property crime trend from 2011 to 2014.**

Figure 3.2 shows the geographical distribution of property crime in Spring 2011 and Winter 2013-14. These seasons had the highest and lowest total property crime counts, respectively. Generally, areas with high property crime counts were clustered in central areas of the study region during Spring 2011, whereas areas with high crime counts during Winter 2013-14 were relatively more dispersed.



**Figure 3.2. Property crime counts for Summer 2011 and Winter 2013-14. The number of DAs in each map class is shown in parentheses.**

Table 3.1 shows descriptive statistics for the seasonal property crime counts at the small-area level. Seasons were defined to follow conventional date ranges (i.e., spring and autumn equinoxes, summer and winter solstices). Note that past research has used a variety of seasonal definitions, including monthly (Andresen and Malleson, 2013; Yan, 2004), bi-monthly (Hipp et al., 2004), every three months (Anderson, 1987), and every five months (Landau and Fridman, 1993). For reference, the study region has a continental climate where summer is the warmest season (average of 19 °C during the study period), followed by spring (10 °C), autumn (5 °C), and winter (-5 °C). Linning (2015) suggests that seasonal crime trends are more pronounced in continental climates than in climates where temperatures are more homogeneous (e.g., coastal climates).

**Table 3.1 Small-area descriptive statistics for twelve seasons of property crime**

Season	Date Range	Mean	SD	Max	DAs with 0
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					crime (%)
Spring 2011	March 20 to June 20	4.46	8.67	142	19.66
Summer 2011	June 21 to September 22	5.83	9.82	159	12.31
Autumn 2011	September 23 to December 21	4.77	8.67	128	17.82
Winter 2011-12	December 22 to March 19	3.88	7.43	104	25.88
Spring 2012	March 20 to June 19	4.75	8.43	124	18.81
Summer 2012	June 20 to September 21	5.40	8.57	142	13.86
Autumn 2012	September 22 to December 20	3.94	8.21	112	25.88
Winter 2013-14	December 21 to March 19	3.36	6.73	74	30.98
Spring 2013	March 20 to June 20	3.97	7.20	107	20.09
Summer 2013	June 21 to September 21	4.70	7.98	111	18.95
Autumn 2013	September 22 to December 20	3.64	9.92	82	27.58
Winter 2013-14	December 21 to March 19	2.81	7.07	102	36.07

Eight distinct land use variables were analyzed: location in a central business district, commercial land use, eating and drinking establishments, government-institutional land use, parks, residential land use, schools, and public transit stations (Andresen and Malleon, 2013; Cohn and Rotton, 2000; di Bella et al., 2015; Kinney et al., 2008; LaGrange, 1999; Linning, 2015; Matthews et al., 2010; Sherman et al., 1989; Stucky and Ottensmann, 2009; Wilcox et al., 2004). Central business districts were delineated by municipally-defined downtown boundaries for the three cities in the study region. Commercial land uses were comprised of retail stores and shopping malls; eating and drinking establishments included restaurants, bars, and pubs; and government-institutional land uses included government buildings and community services (e.g., community centres). Schools included both elementary and secondary schools, and public transit station density was calculated as the number of bus stations per area. Land use data was compiled from the Region of Waterloo, a vector land use

database, and Statistics Canada (2012). Land uses that were infrequent at small-area scales were operationalized as binary variables (see Table 3.2). Note that DAs may have multiple land use types (e.g., a DA may be located in the central business district and have eating and drinking establishments, commercial land uses, and a park). All land use data was obtained for 2011.

**Table 3.2. Descriptive statistics for built environment and sociodemographic characteristics.**

	Mean	SD
<i>Built environment characteristics</i>		
Central business district (binary)	0.02	NA <sup>a</sup>
Commercial (binary)	0.10	NA
Eating and drinking establishments (binary)	0.28	NA
Government-institutional (binary)	0.30	NA
Park (binary)	0.39	NA
Residential (% of area)	68.32	33.31
Schools (binary)	0.14	NA
Public transit stations (density per km <sup>2</sup> )	18.22	16.43
<i>Sociodemographic characteristics</i>		
Residential population (count)	674.91	470.71
Five-year residential mobility (%)	37.57	17.43
Immigrant residents (%)	21.13	10.79
Index of ethnic heterogeneity (0 to 1)	0.52	0.14
Lone-parent families (%)	16.44	8.38
Low-income families (%)	12.14	11.55
Median income (\$)	33,395.57	8,867.95

Young adult population (%)	14.64	5.69
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<sup>a</sup> Standard deviations are not reported for binary variables.

Seven sociodemographic variables were tested to account for neighbourhood disadvantage: residential population size, five-year residential mobility rate, the percent of immigrant residents, the index of ethnic heterogeneity, the percent of lone-parent families, the percent of low-income families, median income, and the percent of young adult population (Table 3.2) (Craglia et al., 2005; Law and Quick, 2013). Residential population was analyzed as an explanatory variable because property crime may be concentrated in small-areas with mostly non-residential land use (i.e., residential population is not a representative population at risk) and because past research has suggested that residential population is a proxy for the number of potential offenders in the routine activity theory (Weisburd et al., 2012; di Bella et al., 2015).

### 3.5. Spatiotemporal modeling

Property crime counts ( $O_{ij}$ ) for small-area  $i$  ( $= 1, \dots, 707$ ) and season  $j$  ( $= 1, \dots, 12$ ) were modeled as independent Poisson random variables conditional on means  $\mu_{ij}$ . In the Bayesian statistical framework, the Poisson distribution is often used to model sparse count data at the small-area scale (Wheeler and Waller, 1997; Richardson et al., 2003; Li et al., 2013). Model 3–1 models the expected counts of property crime ( $\mu_{ij}$ ) as the sum of: an intercept ( $\alpha$ ), a set of spatially structured random effects terms ( $s_i$ ), a set of spatially unstructured random effects terms ( $u_i$ ), a set of temporally structured random effects ( $\lambda_j$ ), and a set of space-time interaction random effects terms ( $\phi_{ij}$ ) (Knorr-Held and Besag, 1998). The random effects terms  $u_i$  and  $s_i$  account for overdispersion and residual spatial autocorrelation of crime counts, respectively (Besag et al., 1991; Haining et al., 2009). The temporally structured random effects terms ( $\lambda_j$ ) capture the residual temporal autocorrelation of

property crime between seasons for the study region. The space-time interaction terms ( $\phi_{ij}$ ) capture extra-Poisson variability not accounted for by other model parameters.

$$\log(\mu_{ij}) = \alpha + s_i + u_i + \lambda_j + \phi_{ij} \quad (3-1)$$

Model 3–2 adds a set of time-constant regression coefficients ( $\kappa$ ) that estimate the associations between property crime and small-area sociodemographic characteristics ( $x_i^{(1)}$ ) and between property crime and small-area land use characteristics ( $x_i^{(2)}$ ). To model the seasonally-varying influences of land use on crime, the regression coefficients associated with land uses are allowed to vary for each time period in Model 3–3 ( $\psi_j$ ). This is informed by previous research observing that sociodemographic characteristics are associated with overall levels of crime, but not seasonal variations (Hipp et al., 2004; Sorg and Taylor, 2011), and assumes that sociodemographic variables only influence the underlying spatial distribution of crime.

$$\log(\mu_{ij}) = \alpha + \kappa x_i^{(1)} + \kappa x_i^{(2)} + s_i + u_i + \lambda_j + \phi_{ij} \quad (3-2)$$

$$\log(\mu_{ij}) = \alpha + \kappa x_i^{(1)} + \psi_j x_i^{(2)} + s_i + u_i + \lambda_j + \phi_{ij} \quad (3-3)$$

The time-varying coefficients in Model 3–3 are specified as the sum of a time-constant component ( $\beta$ ), which estimates the stable influence of land use through all seasonal time periods, and a time-changing component ( $\gamma_j$ ), which estimates the season-specific changes in the associations between land use and crime ( $\psi_j = \beta + \gamma_j$ ). This coefficient structure assumes that land uses, and the routine activities that occur around them, simultaneously influence the underlying spatial distribution of crime and season-specific increases and decreases in crime. Because land use composition did not change substantially during the study period, land use data was treated as constant for all seasons (i.e.,  $x_i^{(2)}$  is not time indexed). Also, note that Model 3–3 can be extended to explore research questions where land use changes over time by including land use data for each time period as  $x_{ij}^{(2)}$ .



Based on the results of Model 3–3, the time-varying relationships for eating and drinking establishments, parks, and public transit station land uses appeared to be recurring such that they were positively or negatively associated with property crime during two consecutive time periods (e.g., spring and summer) for two or more of the three four-season cycles. Model 3–4 quantifies these recurring relationships, where  $v_j$  are modified time-varying coefficients and  $x_i^{(3)}$  are the presence or absence of eating and drinking establishments, the presence or absence of parks, and the density of public transit stations within small-areas. The modified time-varying coefficients ( $v_j = \beta_k + \gamma_j$ ) are the sum of time-constant components that were estimated for each four-season cycle and time-varying components that were estimated for two-season groups (i.e., spring/summer or autumn/winter). To be clear, the time-constant components were  $\beta_k$ , where  $k$  takes the value 1 for the first four-season cycle (Spring 2011 to Winter 2011-12), the value 2 for the second four-season cycle (Spring 2012 to Winter 2012-13), and the value 3 for the third and final four-season cycle (Spring 2013 to Winter 2013-14). For eating and drinking establishments and public transit stations, which were observed to have stronger positive associations with crime in both autumn and winter seasons,  $\gamma_j = 0$  during spring/summer and  $\gamma_j = \delta$  during autumn/winter. Therefore, for these two land uses, the  $\delta$ 's capture the difference between the association during autumn/winter and the baseline association during spring/summer. For parks, which were observed to have a stronger positive association with property crime during the spring and summer,  $\gamma_j = \delta$  during spring/summer, and  $\gamma_j = 0$  during autumn/winter. Therefore, the  $\delta$  for parks captures the differences between the association during spring/summer and the baseline association during autumn/winter. For interpretation, estimates of  $\exp(\delta)$  unambiguously greater or less than 1 indicate a significant difference in effect between spring/summer and autumn/winter time periods.

$$\log(\mu_{ij}) = \alpha + \kappa x_i^{(1)} + \psi_j x_i^{(2)} + v_j x_i^{(3)} + s_i + u_i + \lambda_j + \phi_{ij} \quad (3-4)$$

### 3.5.1. Prior distributions

In Bayesian hierarchical modeling, model parameters are stochastic and assigned prior distributions. A uniform prior distribution was assigned for  $\alpha$  (Thomas et al., 2004). Normal distributions with means of 0 and a common unknown variance was specified for  $u_i$ . The intrinsic conditional autoregressive prior (ICAR) captures residual spatial autocorrelation and was assigned for  $s_i$  (Besag et al., 1991). For the ICAR prior, spatial structure was defined such that areas sharing at least one vertex were considered adjacent. Residual spatial autocorrelation is anticipated because there may be spatially structured risk factors unaccounted for in the model (Tiefelsdorf and Griffith, 2007). Temporally structured random effects ( $\lambda_j$ ) were also assigned ICAR prior distributions, where temporal structure was defined via adjacency between neighbouring seasons (Knorr-Held and Besag, 1998). Because seasonal property crime trend is oscillating (Figure 3.1), this is preferable to prior distributions that constrain time trend to be linear, as in Law et al. (2015). Spatiotemporal interactions ( $\phi_{ij}$ ) were assumed to independently follow a normal distribution with means of 0 and a common unknown variance. This implies that there is no spatial or temporal structure in the residuals after accounting for the other model components.

Regression coefficients  $\kappa$ ,  $\beta$ ,  $\beta_k$ , and  $\delta$  were assigned vague normal prior distributions and, when  $\gamma_j$ 's were treated as unknowns for the land use variables in Model 3–3 and for commercial land uses, the central business district, and schools in Model 3–4,  $\gamma_j$ 's were assigned temporal ICAR distributions with the same adjacency specification as the prior on  $\lambda_j$ . Note that we tested an exchangeable normal prior distribution on  $\gamma_j$  (i.e., no assumption of temporal structure) and obtained very similar results.

Truncated half-normal distributions,  $Normal_{+\infty}(0, 10)$ , were assigned for the prior distribution of the standard deviations of the random effects terms  $s_i$ ,  $u_i$ ,  $\lambda_j$ ,  $\phi_{ij}$ , and for the unknown  $\gamma_j$ 's (Gelman,

2006). Nearly identical results were obtained using two alternative hyperprior distributions assigned on the precisions of random effects, *Gamma* (0.5, 0.0005) and *Gamma* (0.001, 0.001) (Kelsall and Wakefield, 1999).

Models were fit via the Markov chain Monte Carlo algorithm in WinBUGS v.1.4.3. For Models 3–2 and 3–3, all  $\kappa$ 's and  $\psi_j$ 's for which the 95% credible interval (CI) was unambiguously positive or negative for at least six seasons (i.e., did not include zero) were included in the model. The 95% CI is the interval that contains the true value of a parameter with 95% probability. Model convergence occurred after 35,000 iterations and posterior estimates were constructed from two chains run for 50,000 subsequent iterations, where every tenth iteration was retained to reduce autocorrelation of posterior samples. A total of 10,000 iterations were used for obtaining the posterior summary (reported below). Monte Carlo errors for all parameters were below five percent of the corresponding posterior standard deviations, suggesting that the 10,000 iterations were sufficient to approximate the posterior distributions (Lunn et al., 2012). Model fit was evaluated using the Deviance Information Criterion (DIC). The DIC assesses goodness of fit via the posterior mean deviance ( $\bar{D}$ ) and model complexity via the effective number of parameters ( $\rho_D$ ). The model with the smallest DIC value, and with a difference of at least five, is considered to be the best-fitting model (Spiegelhalter et al., 2002).

### **3.6. Results**

Model comparison using DIC is shown in Table 3.3. Adding time-constant covariates for land use and sociodemographic characteristics in Model 3–2 reduced DIC by three points compared to Model 3–1, suggesting that the time-constant covariates did not substantially improve overall model fit. Adding time-varying covariates for all land uses in Model 3–3, however, decreased the DIC by six points from Model 3–2. This provides evidence that modeling the time-varying relationships between land use and crime improved model fit. Model 3–4 had the smallest DIC and was the best-fitting model.

This indicates that modeling the recurring time-varying relationships between property crime and parks, eating and drinking establishments, and public transit stations improved goodness of fit compared to models that estimated a unique relationship for each season for all land use types.

**Table 3.3. Comparing the four spatiotemporal models using DIC.**

Model	$\bar{D}^a$	$p_D^b$	DIC <sup>c</sup>
3-1	29,884	2,571	32,455
3-2	29,893	2,559	32,452
3-3	29,934	2,512	32,446
3-4	29,921	2,518	32,439

<sup>a</sup>  $\bar{D}$  is the posterior mean of the deviance and represents goodness of fit.

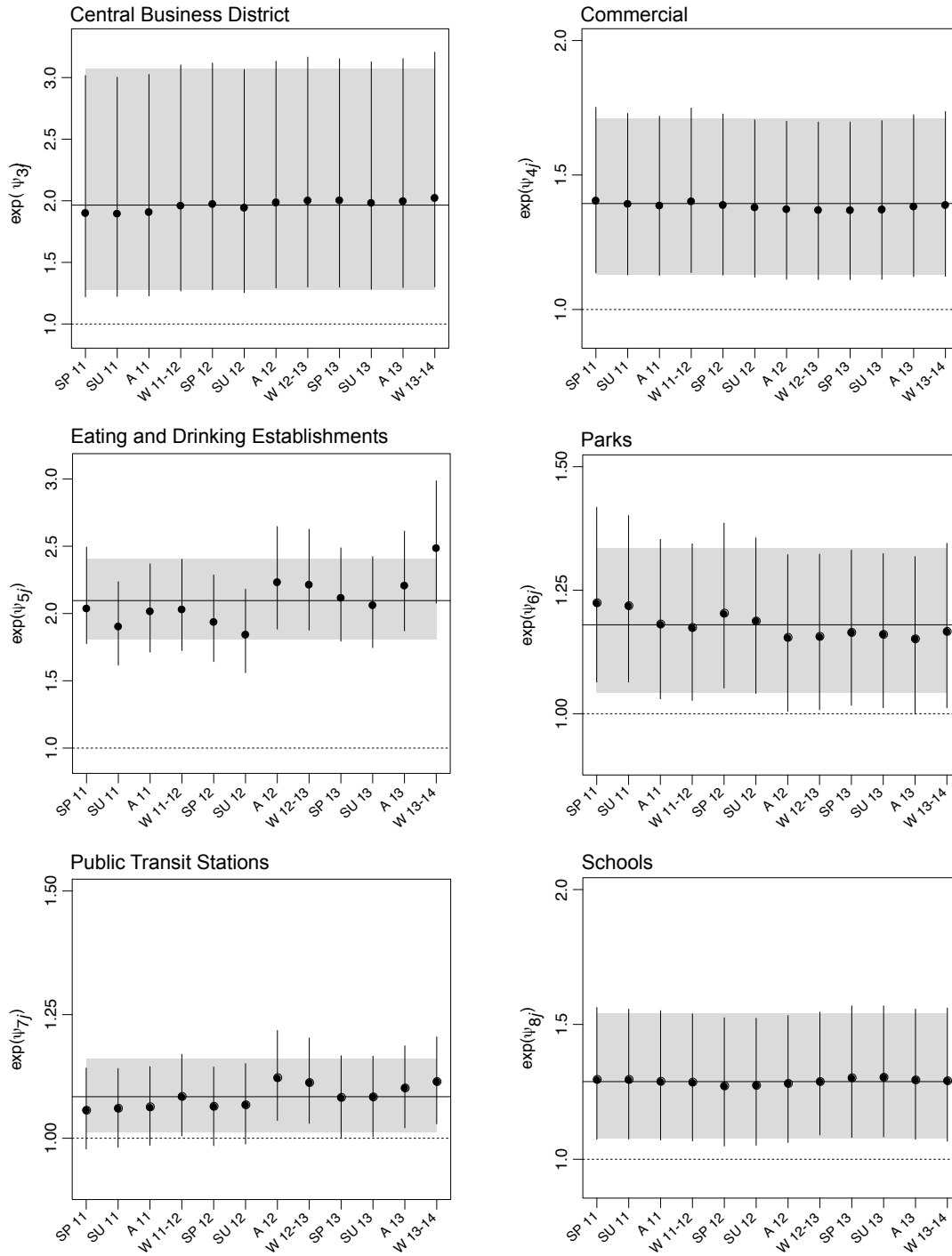
<sup>b</sup>  $p_D$  is the effective number of parameters and represents model complexity.

<sup>c</sup>  $DIC = \bar{D} + p_D$

Table 3.4 shows the time-constant regression coefficients for sociodemographic and land use characteristics from Model 3-3. Regression coefficients are shown as exponential transformations of  $\kappa$  and  $\beta$  (i.e.,  $\exp(\kappa)$  for the time-constant coefficients and  $\exp(\beta)$  for the time-varying coefficients), where values greater than one indicate positive associations with property crime. Two sociodemographic characteristics, residential population and residential mobility, were found to be positively associated with property crime risk at 95% CI. Six built environment characteristics were associated with property crime: location in a central business district, commercial land use, eating and drinking establishments, schools, parks, and public transit stations. All of the land uses were found to be positively associated with property crime for the twelve seasons analyzed. Figure 3.3 visualizes the seasonally-varying relative risks ( $\exp(\psi_j)$ ) for the land uses associated with property crime from Model 3-3.

**Table 3.4. Time-constant coefficient estimates (posterior medians and 95% CI's) for sociodemographic and land use characteristics in Model 3–3.**

	Relative risk (95% CI)
$\alpha$	1.56 (1.43, 1.69)
$\kappa_1$ : Residential population	1.24 (1.16, 1.32)
$\kappa_2$ : Residential mobility	1.15 (1.07, 1.23)
$\beta_3$ : Central business district	1.97 (1.28, 3.07)
$\beta_4$ : Commercial	1.39 (1.13, 1.71)
$\beta_5$ : Eating and drinking establishments	2.09 (1.81, 2.41)
$\beta_6$ : Park	1.18 (1.04, 1.34)
$\beta_7$ : Public transit stations	1.08 (1.01, 1.16)
$\beta_8$ : School	1.29 (1.08, 1.54)



**Figure 3.3. Seasonally varying coefficients for land uses associated with property crime at the DA scale. Posterior medians are shown as points with corresponding 95% CI's shown as vertical bars. SP represents spring, SU represents summer, A represents autumn, and W represents winter. Estimates of time-constant relative risks are indicated by horizontal lines**

**with 95% CI indicated by shaded grey. The horizontal dotted line at  $\exp(\psi_j) = 1$  indicates no relationship between land use and property crime.**

### **3.7. Discussion**

This research has applied a Bayesian spatiotemporal regression modeling approach to investigate if, and how, the relationships between property crime and land use change over time. Controlling for residential population and residential mobility, central business districts, commercial land uses, eating and drinking establishments, schools, parks, and public transit stations were found to be positively associated with property crime risk throughout the twelve-season study period. These land uses have been highlighted in past cross-sectional research exploring the relationships between the built environment and property crime and are commonly interpreted through routine activity theory (Kinney et al., 2008; Matthews et al., 2010; Wilcox et al., 2004).

Central business districts and commercial land uses are representative of small-areas with high concentrations of material goods that may attract motivated offenders regardless of season (Hirschfield and Bowers, 1997). Also, central business districts, commercial land uses, schools, and public transit stations are activity nodes for both obligatory and discretionary activities (LaGrange, 1999). Activity nodes refer to specific locations that attract large numbers of people during routine activities and are anticipated to exhibit positive time-constant associations with property crime (Weisburd et al., 2012: 24). Some proportion of the population moving through these nodes for employment in central business districts, for shopping in areas with commercial land uses, for commuting through areas with high public transit station density, or during discretionary activities for leisure purposes may engage in opportunistic offending when situational conditions arise (i.e., the presence of suitable targets and a lack of capable guardianship) (Brantingham and Brantingham, 2008; Ceccato et al., 2002; Haberman and Ratcliffe, 2015).

In addition to routine activity theory explanations, non-residential land uses have been found to have a positive time-constant relationship with crime because they limit local informal social

control, or the capacity of neighbourhood residents to realize common values (Taylor et al., 1995; Kurtz et al., 1998; Sampson et al., 2002). By attracting strangers and non-residents, business-centred non-residential land uses challenge local resident-based informal social control and contribute to perceptions that residents will not intervene or report suspicious or criminal behaviour (Wilcox et al., 2004; Kurtz et al., 1998). All six of the land use types that were found to be positively associated with time-constant property crime risk are non-residential land uses, and the land uses with the largest time-constant regression coefficients were business-centred non-residential land uses, specifically the central business district, commercial land uses, and eating and drinking establishments (Table 3.4).

### **3.7.1. Recurring relationships between land use and crime**

Focusing on the spatiotemporal relationships between land use and crime, we first classify each land use as to whether they exhibit a recurring or inconsistent relationship with property crime. A recurring trend is a seasonally-varying relative risk trend that repeats a four-month pattern for at least two of three four-season cycles (i.e., eight of twelve months). For example, a recurring trend that repeats over three four-season cycles is property crime count for the study region; property crime is highest in all summer seasons and lowest in all winter seasons (Figure 3.1). An inconsistent trend does not follow a repeating four-month pattern (e.g., consistently increasing throughout twelve seasons). This classification balances the inherent heterogeneity of small-area spatiotemporal data over twelve seasons, the unconstrained specification of time-changing components (i.e., no oscillating trend imposed on  $\lambda_j$  or  $\gamma_j$ ), and past research hypotheses focusing on recurring relationships between land use and property crime.

Based on visual observation of Figure 3.3, three land uses exhibited recurring seasonally-varying relative risk trends at the DA scale: parks, public transit stations, and eating and drinking establishments. Parks were found to have higher positive associations with property crime during spring and summer seasons than during autumn and winter for the first eight seasons.; public transit



stations had higher positive associations during autumn and winter seasons than spring and summer seasons for all twelve seasons analyzed; and eating and drinking establishments had higher positive associations with crime in autumn and winter than in spring and summer for the second and third four-season cycles. Seasonally-varying relative risk trends of central business districts, schools, and commercial land uses at the DA scale were classified as inconsistent.

Table 3.5 shows the results of the modified time-varying coefficients that measure the recurring relationships between property crime and parks, eating and drinking establishments, and public transit stations. The effect of public transit stations in the autumn/winter exhibited a significant departure from the effect during spring/summer for only one time period. This may be attributed to season-specific relative risks for  $j = 1, 2, 3, 5,$  and  $6$  being indistinguishable from zero (95% CI estimates in Figure 3.3) and suggests that, while public transit stations are associated with overall property crime risk, there is little evidence of a recurring seasonal influence of this land use type on small-area property crime.

**Table 3.5. Posterior medians and 95% CI's of the modified time-varying coefficients that estimate the recurring associations between property crime and land uses during spring/summer and autumn/winter.**

	Eating and drinking establishments	Parks	Public transit stations
Spring – Summer 2011	NA <sup>a</sup>	1.14 (1.03, 1.26)	NA
Autumn – Winter 2011-12	1.04 (0.94, 1.15)	NA	1.01 (0.97, 1.06)
Spring – Summer 2012	NA	1.12 (1.01, 1.24)	NA
Autumn – Winter 2012-13	1.24 (1.12, 1.38)	NA	1.09 (1.03, 1.14)
Spring – Summer 2013	NA	1.02 (0.91, 1.14)	NA
Autumn – Winter 2013-14	1.14 (1.02, 1.27)	NA	1.04 (0.99, 1.09)

Parks were found to exhibit a recurring relationship with property crime for two of three spring/summer time periods, specifically in 2011 and 2012 (Table 3.4). This confirms visual observation of seasonally-varying trends in Figure 3.3 and supports past descriptive research observing that property crime rates increase during summer months in areas with parks, beaches, and outdoor public spaces (Andresen and Malleson, 2013; Brunsdon et al., 2009; Linning, 2015). Compared to autumn and winter seasons, spring and summer seasons in the study region are warm and discretionary routine activities, including events and unstructured socializing, are more often located outdoor and in and around public parks. Outdoor events situated at parks include festivals, concerts, public celebrations, and recreational sports leagues. From a routine activity perspective, higher levels of these discretionary activities in small-areas with parks during spring and summer seasons suggests corresponding increases in crime opportunities and property crime offences, including thefts from unoccupied vehicles, thefts from nearby stores, or property damage or graffiti, for example (Rotton and Cohn, 2000).

Eating and drinking establishments also show evidence of a recurring seasonal relationship with property crime, where the associations during Autumn/Winter 2012-13 and Autumn/Winter 2013-14 were significantly different from the preceding spring/summer periods. Throughout the year, eating and drinking establishments, and alcohol serving outlets in particular, are likely to have large numbers of patrons and some proportion may have low self-control related to alcohol consumption (Groff and Lockwood, 2014; Gruenewald et al., 2006). This may be amplified in autumn and winter, when the study region's student population tends to concentrate discretionary leisure activities in areas with many eating and drinking establishments. Note that this finding contrasts with Hipp et al. (2004), who found that eating and drinking establishments were associated with high property crime during the summer for larger geographical units. This suggests that the results of this research may be closely tied to study region composition. The spatiotemporal relationships between eating and

drinking establishments should be further explored using data from many cities, specifically focusing on differentiating a generalizable trend from city-specific variations.

While it is clear that property crime increases during the summer, and while past research has suggested that summertime school holidays/closures are associated with higher property crime risk because youth are unoccupied and more likely to engage in delinquent behaviour (Cohn and Rotton, 2000), the results of this research show that schools do not exhibit a recurring seasonal relationship with crime (Figure 3.3). One explanation for this finding may be that youth not attending school during the summer are responsible for some of the overall increase in property crime during summers, but that the location of crimes are not concentrated around schools (Carbone-Lopez and Lauritsen, 2013). A second explanation may be that, despite seasonal fluctuations in the number of students attending school, land uses such as parks and eating and drinking establishments are included as activity nodes in a larger proportion of the population and therefore experience the largest seasonal variations in offender and target convergences.

### **3.7.2. Spatiotemporal crime patterns and time-varying regression coefficients**

This research is, to the best of our knowledge, the first to directly model the time-varying relationships between neighbourhood characteristics and crime at the small-area scale. This compares with past studies that have compared coefficient estimates from multiple cross-sectional regression models (constructed for each time period) or estimated the interactions between small-area characteristics and indicator variables of time, such as month or temperature (Haberman and Ratcliffe, 2015; Sorg and Taylor, 2011). As such, we reflect on the implications of this research for understanding spatiotemporal crime patterns and the routine activity theory, and outline how this research may be operationalized by urban planning and law enforcement professions.

This research suggests that the built environment has a more substantial influence on spatial, rather than spatiotemporal, crime patterns. Results from Models 3–3 show that the magnitude of the

time-varying components are relatively modest compared to time-constant components for all land uses, and that the posterior medians of the time-varying regression coefficients were generally within the 95% CI's of the time-constant components. From Figure 3.3, for example, only two season-specific risk estimates were at least five percent greater than time-constant estimates: eating and drinking establishments during Winter 2013-14 (18.7% greater than time-constant risk) and during Summer 2012 (12.02% less than time-constant risk). This is further supported by variance partition coefficients (VPC), which quantify the proportion of spatiotemporally variation of property crime explained by spatial random effects, temporal random effects, and space-time interaction terms in Model 3-1, and by both random effects and covariates in Models 3-2, 3-3, and 3-4 (Goldstein et al., 2002). For example, the VPC for spatial random effects in Model 3-1, is equal to the sum of the empirical variances of  $u_i$  and  $s_i$  divided by the sum of the empirical variances of  $u_i$ ,  $s_i$ ,  $\lambda_j$ , and  $\phi_{ij}$ . In Model 3-1, 86% of the overall variability of property crime was due to the consistent spatial pattern (sum of spatially structured and unstructured random effects). When adding time-constant land use and sociodemographic covariates in Model 3-2, the VPC of spatial random effects decreased from 86% to 62%, with approximately 15% now explained by land use and about 7% now explained by sociodemographic characteristics. When adding time-varying land use covariates in both Models 3-3 and 3-4, however, the proportions of variability explained by land use characteristics remained at approximately 15% and there were no substantial changes to the VPCs of the sociodemographic variables or the spatial, temporal, and space-time random effects terms. See Appendix F for full VPC results.

From a theoretical perspective, the structure of time-varying coefficients parallels the distinction between obligatory and discretionary activities in routine activity theory. Time-constant components represent obligatory activities and time-changing components represent season-specific changes in discretionary activities (Tompson and Bowers, 2015). Because time-constant and time-

changing components are often similar in magnitude, it appears that the degree to which discretionary activities, as inferred through land use composition, influence small-area property crime is relatively minor. This is not unexpected, as we simultaneously account for sociodemographic characteristics as well as the time-varying effects of multiple land uses, and it is possible that past descriptive research has overstated the role of land use in driving seasonal crime trends. Alternatively, it is possible that land use is not representative of spatiotemporal variations in discretionary routine activities and, instead, it is more suitable for understanding the time-constant or spatial distribution of obligatory routine activities. One analytical challenge associated with spatiotemporal modeling of built environment data for three years is that land use change, at a scale substantial enough to be captured in analysis of many small-areas, occurs over long periods of time. As a result, we analyzed constant land use data for the study period, and this may be another explanation for relatively small departures of the seasonally-varying estimates from the time-constant estimates.

### **3.7.3. Spatiotemporal property crime trends and policy applications**

This research informs crime reduction and prevention initiatives in both urban planning and law enforcement. Urban planning, in particular, has the potential to reduce time-constant property crime risk in specific small-areas as the effects of land use on property crime are predominately spatial, rather than spatiotemporal. As Johnson et al. (2008) argue, when spatiotemporal crime patterns are relatively consistent over time, permanent changes to the built environment may be more effective for crime reduction than interventions focused on temporary or cyclic changes in police patrol location and frequency.

One planning strategy to reduce property crime risk may be to limit future development of high-risk land uses in neighbourhoods with high time-constant property crime risk, or in areas located in the central business district and with high concentrations of eating and drinking establishments (i.e., largest  $\beta$ 's in Model 3–3). However, because these land use characteristics, and many of the

other land use types found to be positively associated with property crime are desirable amenities and serve important functions, a better option may be to implement crime prevention through environmental design standards (CPTED). CPTED aims to influence offender decision-making by increasing perceptions of capable guardianship and interacts with land use to shape the opportunity structures for crime highlighted by the routine activity theory (Greenberg and Rohe, 1984). In a spatiotemporal context, urban planners should consider how the physical characteristics and activity functions of land uses change over time (Groff and McCord, 2011). For example, urban planners and designers may look to ensure that foliage and infrastructure in parks during the summer does not obscure the natural surveillance, or the ‘eyes on the street’, provided by vehicular traffic, passersby, and park users (Jacobs, 1961; Loukaitou-Sideris et al., 2001; Iqbal and Ceccato, 2016).

Compared to the relatively permanent built environment modifications that result from land use planning and urban design, law enforcement can change the spatial and temporal distribution of resources in anticipation of recurring seasonal crime trends (Johnson et al., 2008). The results of this research suggest that the geographical distribution of law enforcement resources should be relatively consistent throughout the year and target neighbourhoods that have land uses with high time-constant associations with property crime, as the stable spatial pattern is most important in explaining the overall spatiotemporal variability of property crime. Temporally, moderate amounts of law enforcement resources may be cycled between areas with parks in the spring/summer and areas with eating and drinking establishments in the autumn/winter. Public awareness campaigns and targeted policing initiatives may prevent and deter crime, influencing time-constant and season-specific crime risk in the targeted small-areas and the study region as a whole.

#### **3.7.4. Limitations and future research**

One limitation of this research is that land use composition is operationalized to represent behavioural routine activity patterns. This is common in spatial analyses of crime; however, it is possible that land

use is not representative of spatiotemporal routine activity patterns (Brantingham and Brantingham, 2008; Kinney et al., 2008; Matthews et al., 2010; Smith et al., 2000). Future research should investigate data that directly captures both spatial and temporal dimensions of routine activities, such as sales data from commercial retail stores (Weisburd et al., 2012), statistics on park users or transit ridership (Loukaitou-Sideris et al., 2001), or mobile phone and social media data that captures business check-ins (Hanaoka, 2016; Jacobs-Crisioni et al., 2014). It may also be interesting to explore spatiotemporal crime patterns during longer processes of metropolitan or neighbourhood change, for example, modeling the time-varying effects of changing sociodemographic characteristics related to gentrification (Kirk and Laub, 2010; Papachristos et al., 2011).

A second limitation of this research is that the time-varying relationships between land use and crime are estimated for the entire study region. Modeling seasonal relative risk trends for the study region improves understanding of the processes influencing spatiotemporal crime patterns but may overlook geographically and temporally-focused variations in crime. For example, outdoor events hosted in one park that increase property crime in nearby neighbourhoods for a small period of time may be obscured in this spatiotemporal model. In future research, the time-varying relationships between neighbourhood characteristics and crime should be investigated at the small-area level using regression coefficients vary over both space and time. One approach would be to develop Bayesian spatially- and temporally-varying coefficient models, which may resemble the non-Bayesian method proposed by Fotheringham et al. (2015). Furthermore, research may look to incorporate additional land use-specific data in spatiotemporal analyses, such as whether parks have playgrounds or event spaces, to develop more specific understanding how parks are used, and the behavioural mechanisms associated with crime (Wilcox et al., 2004; Groff and McCord, 2011).

Related, we assume that sociodemographic characteristics do not influence seasonal variations of crime. While this is supported by past time-series research analyzing property crime trends using the routine activity theory (Hipp et al., 2004), it is possible that neighbourhood crime

trends are influenced by neighbourhood disadvantage and residential mobility, for example. Studies have shown that violent crimes tend to concentrate in disadvantaged neighbourhoods during the summer, as explained by the interactions between uncomfortably high temperatures, aggression, and disadvantage (Harries et al., 1984; Rotton and Cohn, 2004). The time-varying coefficients used in this study would be useful for exploring how the relationships between violent crime and sociodemographic contexts vary over time. Finally, the results of this research should be taken in context of the modifiable areal and temporal unit problems (Openshaw, 1984; Cheng and Adepeju, 2014). The time-varying relationships between land use and crime will exhibit different trends depending on how seasonal time periods and small-area units are defined and alternative operationalizations of spatial and temporal units should be further investigated.



## **Chapter 4: Multiscale spatiotemporal patterns of crime: A Bayesian cross-classified multilevel modeling approach**

### **4.1. Summary**

Characteristics of the urban environment influence where and when crime events occur, however, past studies typically analyze cross-sectional data for one spatial scale and do not account for the processes and place-based policies that influence crime across multiple scales. This research applies a Bayesian cross-classified multilevel modelling approach to examine the spatiotemporal patterning of violent crime at the small-area, neighbourhood, electoral ward, and police patrol zone scales. Violent crime data are measured at the small-area scale (lower-level units) and small-areas are nested in neighbourhoods, electoral wards, and patrol zones (higher-level units). The cross-classified multilevel model accommodates multiple higher-level units that are non-hierarchical and have overlapping geographical boundaries. Results show that violent crime is positively associated with population size, the central business district, and socioeconomic disadvantage within small-areas and negatively associated with civic engagement within electoral wards. Combined, the three higher-level units explain approximately fourteen percent of the total spatiotemporal variation of violent crime. Neighbourhoods are the most important source of variation amongst the higher-level units. This study advances understanding of the multiscale processes influencing spatiotemporal crime patterns and provides area-specific information within the geographical frameworks used by policymakers in urban planning, local government, and law enforcement.

### **4.2. Introduction**

Spatiotemporal crime patterns are influenced by characteristics of the urban environment at multiple spatial scales (Ouimet, 2000; Wooldredge, 2002; Boessen and Hipp, 2015). Studies that explore local crime patterns, however, often analyze cross-sectional data for a single set of geographical units.

Focusing on one spatial scale overlooks the complex spatial structure of urban areas and does not account for the relationships between crime and sociodemographic, political, and built environment characteristics across multiple spatial scales (Sampson, 2013). From a theoretical perspective, analyzing local crime patterns at two or more spatial scales provides insight into the crime-generating processes that arise over different geographical contexts and helps to distinguish which spatial scale is most important for understanding where and when crime events occur (Taylor, 2015; Steenbeek and Weisburd, 2016). From a policy perspective, incorporating the multiple geographical frameworks used by local government and law enforcement into quantitative analyses enables policy-relevant information to be estimated and the most suitable spatial scales for crime prevention interventions to be assessed.

This research applies a Bayesian cross-classified multilevel modelling approach to examine the spatiotemporal patterning of violent crime over five years at the small-area, neighborhood, electoral ward, and police patrol zone scales. Crime data are measured at the small-area scale (lower-level units) and small-areas are nested in neighbourhoods, electoral wards, and patrol zones (higher-level units). Neighbourhoods, electoral wards, and patrol zones are non-hierarchical such that the set of small-areas nested in one neighbourhood may also be nested in two or more electoral wards and two or more patrol zones (Goldstein, 1994; Browne et al., 2001). For spatiotemporal crime analyses, cross-classified multilevel models provide a framework for integrating two or more higher-level contexts with overlapping geographical boundaries, for estimating the effects of observed and latent covariates at both lower- and higher-levels, and for quantifying the degree to which the spatiotemporal variation of crime is explained by each set of geographical units.

This study illustrates the first application of a multilevel cross-classified model to analyze the spatiotemporal patterning of crime. In this study, violent crime was found to be positively associated with sociodemographic, built environment, and civic engagement covariates at multiple scales, and neighbourhoods, electoral wards, and patrol zones were found to account for approximately fourteen

percent of the total spatiotemporal variation of violent crime. This advances past research that characterizes the distribution of crime at one spatial scale by showing that local crime patterns are simultaneously influenced by characteristics of the urban environment at multiple scales (Ouimet, 2000; Wooldredge, 2002). Also, this study extends past multilevel analyses of crime patterns by estimating the area-specific effects for multiple overlapping higher-level units that are each relevant for theoretical inference and for policy development in urban planning (neighbourhoods), local government (electoral wards), and law enforcement (patrol zones) (Steenbeek and Weisburd, 2016; Schnell et al., 2017). In the following sections of this paper, the theories and methods used to explain and analyze multiscale crime patterns in past research are reviewed, the data and the Bayesian multilevel modelling approach are detailed, the results of this study are shown, and contributions of this study for theory and crime prevention policy are discussed.

### **4.3. Theoretical review**

Local spatial and spatiotemporal patterns of violent crime are commonly explained by social disorganization theory, collective efficacy theory, and routine activity theory (Miethe et al., 1991; Braga and Clarke, 2014). Social disorganization theory hypothesizes that structural characteristics influence the development and maintenance of resident-based informal social control, which, in turn, shapes the degree to which community members mobilize to control criminal behaviour (Shaw and McKay, 1942). Informal social control is defined as the capacity to develop and maintain a common set of values and norms and is operationalized by variables measuring socioeconomic disadvantage, residential mobility, and ethnic heterogeneity, as high levels of these characteristics are thought to challenge the formation of social ties between residents and limit the degree to which community members can establish shared values and norms (Sampson and Groves, 1989; Veysey and Messner, 1999; Kubrin and Weitzer, 2003). While social disorganization theory was originally proposed to describe the residential locations of juvenile delinquents in Chicago (Shaw and McKay, 1942), past

research has applied social disorganization theory to explain the geographical distribution of violent crime offenses across a variety of spatial scales, including municipally-defined neighbourhoods, neighbourhood clusters (aggregations of multiple census tracts), census tracts, and smaller census area units (Ouimet, 2000; Weisburd et al., 2012; Sutherland et al., 2013; Law et al., 2015).

Elaborating on the ways in which informal social control is established and enforced within and between communities, the systemic model of social disorganization contends that social control functions at private, parochial, and public levels. Private social control manifests through the intimate relationships between friends and family, parochial social control results from the non-intimate relationships between community residents, and public social control is established through the relationships between communities and extra-local organizations (Bursik Jr. and Grasmick, 1993). Geographically, the three levels of social control are hierarchical; private social control is exercised at the micro-scale within households or friendship networks, parochial social control operates at the meso-scale within small-area units, and public social control functions within larger geographical units, such as municipally-defined neighbourhoods or community areas (Taylor, 1997; Wooldredge, 2002). Distinguishing between the meso- and macro-scales of social control, in particular, past studies have suggested that parochial social control is most appropriately inferred via sociodemographic structural characteristics for small-areas and that public social control can be operationalized by variables that capture community-level civic engagement and/or actions that work to secure political and economic resources from local government and law enforcement (Velez, 2001; Kubrin and Weitzer, 2003; van Wilsem et al., 2006).

Collective efficacy theory hypothesizes that crime patterns are explained by both informal social control and the willingness of residents to intervene on behalf of the common good (Sampson et al., 1997). Collective efficacy theory extends social disorganization theory by recognizing that local criminal behaviour is shaped by the common values shared amongst residents as well as the degree to which community members will take task-specific actions to achieve collective goals, such

as living in a safe environment (Sampson et al., 1997; Morenoff et al., 2001). Predominately operationalized for groups of census tracts and municipally-defined neighbourhoods, collective efficacy research often analyzes the structural characteristics highlighted by social disorganization theory as well as survey data that asks about social cohesion and perceptions that community members will intervene in suspicious, disorderly, or criminal behaviour (Sampson et al., 1997; Sutherland et al., 2013). When representative survey data for all geographical units within an urban area is unavailable, however, researchers have inferred collective efficacy via variables that capture local civic engagement, such as the percent of active voters, because this is an indicator of the degree to which residents engage in public affairs and take action to achieve shared goals (Weisburd et al., 2012). Related, civic engagement has also been highlighted as a dimension of social capital, or the cooperative relationships between people that facilitate action towards collective goals, with past studies showing that the percent of active voters is negatively associated with crime after accounting for social disorganization covariates (Rosenfeld et al., 2001; Coleman, 2002).

The third theoretical perspective used to explain local crime patterns is routine activity theory. Routine activity theory contends that crime offenses occur when motivated offenders, suitable targets, and a lack of capable guardianship converge in space and time (Cohen and Felson, 1979). Compared to social disorganization and collective efficacy theories, which focus on the social dynamics within neighbourhoods, routine activity theory centres on how the behavioural activities of potential offenders and potential victims interact with characteristics of the physical environment. Situating routine activity theory at multiple spatial scales, Brantingham and Brantingham (1993) propose that crime patterns are simultaneously influenced by activity nodes, activity paths, and the environmental backcloth. Activity nodes are specific locations where large populations come together for daily activities – such as non-residential areas used for employment, school, or shopping – activity paths are the travel routes between activity nodes – such as public transit stations and major roads – and the environmental backcloth is composed of the broader social, political, and physical contexts in

which activity nodes and paths are located (Groff et al., 2010; Deryol et al., 2016). Broadly, past research has found that areas with high traffic activity nodes and/or paths have relatively higher crime rates than areas without nodes and/or paths or areas with low traffic nodes and/or paths (Wilcox and Eck, 2011).

Combined, social disorganization, collective efficacy, and routine activity theories provide a theoretical background for understanding the multiscale structure of local crime patterns. Consider, for example, a group of adjacent small-areas nested in larger zones used for urban planning and law enforcement purposes. The larger zones have overlapping geographical boundaries such that the group of small-areas nested in one planning zone are simultaneously nested in two different law enforcement zones (i.e., the larger zones are non-hierarchical). In each small-area, violent crime may be influenced by the presence of a high traffic activity node and corresponding convergences between offenders and targets (routine activity theory), as well as structural characteristics and informal social control (social disorganization and collective efficacy theories). In addition to the small-area processes, however, there may be additional high (or low) clustering of crime common to the small-areas nested in the urban planning zone due to planning policy (e.g., similarities in land use composition, housing, or the presence of an activity path) or public social control (e.g., place-based resources attained from local government). Furthermore, there may be distinct clustering of crime amongst the small-areas nested in each law enforcement zone that is attributable to differences in law enforcement practices (e.g., frequent and proactive police patrols) or the relationships between police and community members (public social control).

#### **4.4. Methods for analyzing multiscale crime patterns**

Existing studies that examine spatial and spatiotemporal crime patterns across multiple spatial scales have adopted four methodological approaches: the spatial point pattern test, single-level cluster detection methods, single-level regression models, and multilevel models of purely hierarchical data

(i.e., lower-level spatial units nested in one higher-level unit). The spatial point pattern test quantifies the similarity of two geographically-referenced point datasets at the area-scale by iteratively sampling a subset of points from one dataset (i.e., crime for one year at one scale), establishing area-specific confidence intervals based on the sampled data, and calculating the percent of areas for which the second dataset (i.e., crime for a different year at the same scale) fall within the confidence intervals from the sampled dataset. For multiscale analysis, the spatial point pattern test has been used to examine if the similarity of between-year crime patterns for large areas is different from the similarity of between-year crime patterns for the nested smaller areas (Andresen and Malleson, 2011). While the spatial point pattern test helps to assess if there is variation in crime change at different scales, it does not explain the spatiotemporal patterning of crime through observed or latent covariates across any of the scales (Steenbeek and Weisburd, 2016).

Past studies that explore multiscale crime patterns via single-level cluster detection methods typically compare the locations, sizes, and shapes of clusters identified separately for two or more scales. For example, Andresen (2011) used local Moran's I to compare violent crime clusters for two areal scales using ambient and residential populations as crime rate denominators, finding that, while the cluster locations were similar for both scales, the smaller scale clusters were relatively more sensitive to the crime rate denominator. Similarly, studies that use single-level regression models generally compare model results and diagnostics from separate models fit to data aggregated at different scales. Ouimet (2000), for example, applied separate regression models to explore juvenile violent crime rates for census tracts and larger municipally-defined neighbourhoods and found that the neighbourhood-level model estimated larger regression coefficients and had greater explanatory power. Comparing and contrasting the results of single-level analyses provides insight regarding the scale at which risk factors are associated with crime, however these approaches do not account for the simultaneous effects of risk factors operating across multiple spatial scales.

Multilevel modelling approaches provide a framework for analyzing hierarchically-structured data where lower-level units are nested in higher-level units. To date, few studies have applied multilevel modelling approaches to explore the multiscale spatiotemporal patterns of crime for a comprehensive set of geographical units in an urban area, and instead, the most common use of multilevel models has been to examine the interactions between individual or household characteristics and neighbourhood contexts (van Wilsem et al., 2006; Taylor, 2015). Focusing on a comprehensive set of units in a city, Steenbeek and Weisburd (2016) and Schnell et al. (2017) both used a three-level linear mixed model to examine total crime for street segments, neighbourhoods, and districts/community areas, and found that the lower-level units (street segments) explained the largest proportions of variation. Johnson and Bowers (2010) and Davies and Johnson (2015) applied three-level Poisson models with street segments nested in small-areas nested in larger areas, and observed that street attributes, such as permeability and potential usage, were positively associated with burglary.

The multilevel models used in past studies have analyzed purely hierarchical data where lower-level units are nested in one higher-level unit (e.g., street segments are nested only in neighbourhoods (Steenbeek and Weisburd, 2016)). Cross-classified multilevel models, in contrast, accommodate data where lower-level units are nested in two or more non-hierarchical higher-level units (Goldstein, 1994). Cross-classified multilevel models facilitate the integration of data collected using different geographical frameworks, such as sociodemographic data available for census areas and civic data available for political boundaries, and allow for the analysis of multiple sets of overlapping higher-level areas that are each thought to have distinct data-generating processes. Cross-classified models are also advantageous for policy applications as they can estimate the area-specific effects of both lower- and higher-level units and can quantify the degree to which each spatial scale explains the overall spatial and/or spatiotemporal variation of crime.

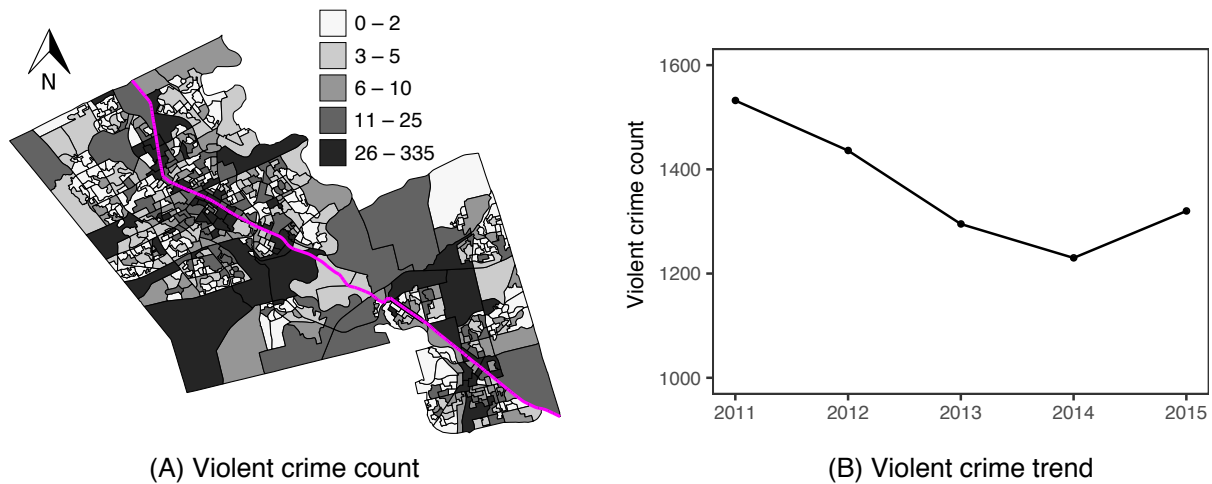


## **4.5. Study region and data**

The Region of Waterloo is located in Ontario, Canada, and is composed of the cities of Cambridge, Kitchener, and Waterloo. The lower-level unit of analysis was the dissemination area (DA) and the higher-level units of analysis were the neighbourhood, electoral ward, and police patrol zone. DAs are the smallest census areas that cover the entirety of Canada and are delineated such that average residential populations are between 400 and 800. In the 2016 Canadian census, there were 656 DAs in the study region with an average residential population of 724 and an average size of 0.49 km<sup>2</sup> (Figure 4.1). Crime, sociodemographic, and built environment data were analyzed at the DA scale and a covariate measuring civic engagement was included at the electoral ward scale. A detailed map of the study region is shown in Appendix A.

### **4.5.1. Crime, sociodemographic, and built environment data**

Reported violent crime incidents were retrieved from the Waterloo Regional Police Service for five years, from 2011 to 2015. Reported incidents were aggregated from street intersections to small-areas. Violent crime counts were the sum of assault incidents and robbery incidents. Total violent crime counts at the DA scale are shown in Figure 4.1 (see Appendix H for descriptive statistics). In general, DAs with high counts of violent crime were clustered around the central commercial corridor as well as in peripheral areas located in the west and southwest. Temporally, violent crime decreased by sixteen percent during the five-year study period, with a decline of approximately twenty percent between 2011 and 2014 and an increase of about seven percent from 2014 to 2015 (Figure 4.1).



**Figure 4.1. Total violent crime counts at the DA scale (A) and the five-year violent crime trend (B). The central commercial corridor is highlighted on the map in A.**

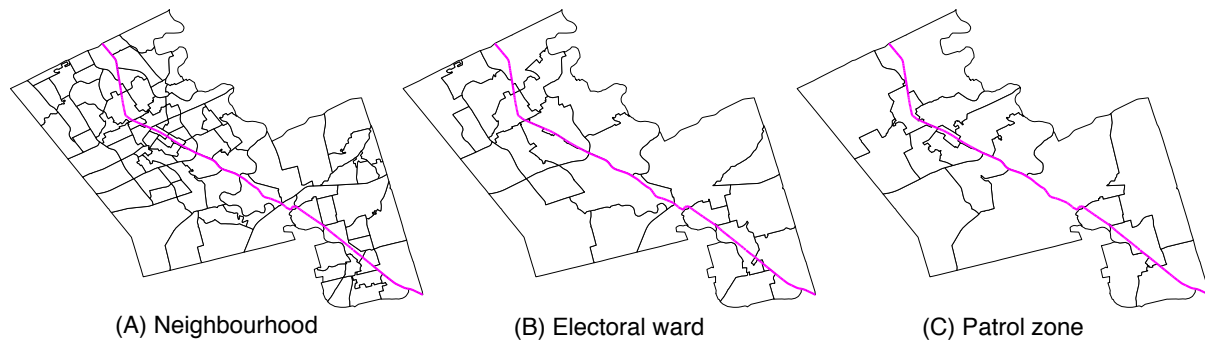
Twelve sociodemographic and built environment variables were selected for analysis at the DA scale based on past research exploring the relationships between crime and the urban environment. Two of the twelve variables, residential population size and the central business district, were directly included in the regression models. Following past studies using generalized linear (Poisson) regression models for analyzing spatial and spatiotemporal crime counts (Ceccato et al., 2018; Quick et al., 2018a; Quick et al., 2018b), residential population was included as an explanatory variable for two reasons. One, because there was no clear definition of the population at risk as violent crime offenders and targets are mobile. Two, because assuming that areas with larger residential populations will have higher levels of crime, which is implied when residential population is used to construct crime rates for regression models requiring continuous dependent variables, may not be appropriate when crime is geographically clustered in areas with small residential populations (e.g., in central business districts, in suburban commercial areas, or in industrial areas) (Malleon and Andresen, 2015). The central business districts for the three cities in the study region were operationalized as a binary variable, where DAs inside the central business district were assigned a value of one and all other DAs were assigned a value of zero.

Ten of the twelve explanatory variables were treated as indicators of four latent factors representing residential instability, socioeconomic disadvantage, family disruption, and ethnic heterogeneity. Residential instability was operationalized as the percent of renters and the five-year residential mobility rate, and socioeconomic disadvantage was measured via the median after-tax household income, the percent of low-income households, the unemployment rate, and the percent of total income received from government transfer payments (Morenoff et al., 2001; Law and Quick, 2013). Family disruption was a latent factor constructed from the percent of single parent families and the percent of divorced or separated households, and ethnic heterogeneity was operationalized via the index of ethnic heterogeneity and the index of language heterogeneity (Sampson and Groves, 1989; Veysey and Messner, 1999; Hipp, 2007). For reference, the indices of ethnic and language heterogeneity quantify the relative mix of ethnicities and languages spoken within DAs and have values that range between zero (less heterogeneity) and one (more heterogeneity). Descriptive statistics for the explanatory variables are shown in Appendix H and the factor analytic models are detailed in Appendix I.

#### **4.5.2. Neighbourhoods, electoral wards, and patrol zones**

Neighbourhoods, electoral wards, and police patrol zones were the higher-level units of analysis (Figure 4.2). Each of the three sets of higher-level units covered the entirety of the study region and so each DA was nested in one neighbourhood, one electoral ward, and one patrol zone. Because the boundaries of the three higher-level units were overlapping, however, the group of DAs within one neighbourhood could belong to multiple electoral wards and/or multiple patrol zones. Most DA boundaries directly aligned with the boundaries of neighbourhoods, electoral wards, and police zones, however, for the few DA boundaries that were misaligned with the higher-level boundaries, DAs were assigned to the neighbourhood, electoral ward, or police zone in which the largest proportion of area was located. In the study region, there were 97 neighbourhoods with an average area of 3.29

km<sup>2</sup>, 25 electoral wards with an average area of 12.76 km<sup>2</sup>, and 18 police zones with an average area of 17.73 km<sup>2</sup>. Neighbourhoods included an average of 6.77 DAs, electoral wards included an average of 26.24 DAs, and police zones included an average of 36.44 DAs.



**Figure 4.2. The geographical boundaries of the three higher-level units. The central commercial corridor is highlighted on all maps.**

Each of the higher-level units is relevant for theoretical inference and for policy applications in urban planning (neighbourhoods), local government (electoral wards), and law enforcement (patrol zones). Defined by the three municipal governments and the three urban planning departments in the study region, neighbourhoods are used for a variety of administrative and policy purposes including neighbourhood associations, which are resident-led organizations that coordinate local programs and events, and secondary land use plans, which provide detailed guidelines for urban development, infrastructure, and environmental services. Past research has suggested that municipally-defined neighbourhoods are suitable for analyzing public social control because this is often the scale at which the economic and political decisions of private and public actors are realized (e.g., via urban planning policies and investments in housing) (Wooldredge, 2002; Sampson, 2013). Also, because neighbourhoods are used for local land use policies, the DAs located in a given neighbourhood are likely to have more similar land use compositions and routine activity patterns than nearby DAs located in different neighbourhoods.

Electoral wards are delineated by the local governments in the study region and are used for the elections of regional representatives, city mayors, and city councillors. From a theoretical perspective, electoral wards are appropriate for operationalizing public social control and collective efficacy because they represent the geographical areas through which residents and communities engage with political representatives on local issues (e.g., emergency services, by-law enforcement) and work with government to secure external resources on behalf of the common good (e.g., public space amenities, funding for community programs) (Rosenfeld et al., 2001; Weisburd et al., 2012). From a practical perspective, data measuring the percent of active voters in the 2014 municipal/regional elections were available for electoral wards and, as such, the effects of civic engagement on violent crime could be analyzed without changing the scale of the data.

Police patrol zones are defined by Waterloo Regional Police Services and are constructed to optimize the delivery of police services. Patrol zones were included in this study to account for potential geographical differences in law enforcement resources, policing tactics, and the relationships between community members and law enforcement (Hagan et al., 1978; Velez, 2001). For example, it is possible that a higher proportion of crime events are reported to, or observed by, police in areas with a more visible police presence, such as in downtown areas where patrols are more frequently done on foot (Klinger and Bridges, 1997). Furthermore, there may be differences in reported violent crimes that parallel the variations in police confidence and/or legal cynicism that are due to the interactions between police and community members within a patrol zone (Goudriaan et al., 2006; Kirk and Matsuda, 2011).

#### **4.6. Multilevel modelling of spatiotemporal crime patterns**

Let  $O_{it}$  represent the observed violent crime counts for DA  $i$  ( $= 1, \dots, 656$ ) and year  $t$  ( $= 1, \dots, 5$ ). Each DA is nested in one neighbourhood  $j_1$  ( $= 1, \dots, 97$ ), one electoral ward  $j_2$  ( $= 1, \dots, 25$ ), and one police patrol zone  $j_3$  ( $= 1, \dots, 18$ ), and so the observed spatiotemporal violent crime counts in all

lower- and higher-level units are denoted by  $O_{it(j_1j_2j_3)}$ . The parentheses surrounding  $j_1, j_2,$  and  $j_3$  indicate that neighbourhoods, electoral wards, and patrol zones are non-hierarchical and analyzed at the same level (Rasbash and Goldstein, 1994).  $O_{it(j_1j_2j_3)}$  were modeled as independent Poisson random variables conditional on mean  $\mu_{it(j_1j_2j_3)}$ . The Poisson model is often used in Bayesian spatial and spatiotemporal modelling of small-area count data (Waller et al., 1997; Congdon, 2003; Haining et al., 2009). The models used to analyze the multiscale patterns of violent crime are described below. Model 4–1 is a single-level model that analyzes the spatiotemporal variation of crime across DAs (i.e., no terms indexed by  $j_1, j_2,$  or  $j_3$ ).

In Model 4–1, the expected crime counts for each DA ( $\mu_{it}$ ) were modeled as the sum of an intercept ( $\alpha$ ), a set of covariates for the observed explanatory variables and latent constructs ( $\beta x_i$ 's and  $\kappa \psi_i$ 's), a set of spatially unstructured random effects terms ( $u_i$ ), a set of temporal terms ( $\zeta_t$ ), and a set of space-time random effects terms ( $\theta_{it}$ ). The regression coefficients denoted by  $\beta_p$  ( $p = 1, 2$ ) quantify the relationships between crime and residential population and the central business district. The regression coefficients denoted by  $\kappa_n$  ( $n = 1, \dots, 4$ ) quantify the relationships between crime and the four latent constructs representing residential instability, socioeconomic disadvantage, family disruption, and ethnic heterogeneity. The spatially unstructured random effects terms capture overdispersion of violent crime counts and the residual within-DA variability of crime, the temporal terms capture the overall crime trend for the study region, and the space-time random effects terms capture extra-Poisson heterogeneity that is not modeled via the other model parameters.

$$\log(\mu_{it}) = \alpha + \beta_p x_{pi} + \kappa_n \psi_{ni} + u_i + \zeta_t + \theta_{it} \quad (4-1)$$

In Model 4–2, the multilevel structure of DAs nested in neighbourhoods, electoral wards, and patrol zones is modeled through the addition of three sets of higher-level random effects terms and one higher-level covariate. The higher-level covariate quantifies the relationship between violent

crime and the percent of voters at the electoral ward scale ( $\lambda\omega_{(j_2)}$ ) and the random effects terms capture the variation of violent crime that is attributed to DAs being grouped in neighbourhoods ( $\gamma_{1(j_1)}$ ), electoral wards ( $\gamma_{2(j_2)}$ ), and patrol zones ( $\gamma_{3(j_3)}$ ) (Langford et al., 1999). For interpretation, the intercept ( $\alpha$ ) captures the overall mean of violent crime across all lower- and higher-level units and the higher-level random effects terms ( $\gamma_{1(j_1)}$ ,  $\gamma_{2(j_2)}$ , and  $\gamma_{3(j_3)}$ ) capture the differences between the overall mean and the neighbourhood-, electoral ward-, and police zone-specific means of violent crime after accounting for the explanatory variables (Leckie, 2013). For example, neighbourhoods with large values of  $\gamma_1$  will tend to be composed of DAs that have relatively high violent crime and police patrol zones with small values of  $\gamma_3$  will tend to be composed of DAs that have relatively low violent crime. Note that Model 4–1 and Model 4–2 were tested with a set of spatially structured random effects (assigned an intrinsic conditional autoregressive prior distribution with a first-order queen contiguity matrix) to capture residual spatial autocorrelation between DAs (Besag et al., 1991; Arcaya et al., 2012; Dong and Harris, 2015). However, the spatially structured random effects terms did not converge, did not improve model fit, and were not included in the final models. Model 4–1 and 4–2 were also tested with unstructured space-time random effects terms for the higher-level units but adding these parameters did not improve model fit.

$$\log(\mu_{it(j_1j_2j_3)}) = \alpha + \beta_p x_{pi} + \kappa_n \psi_{ni} + u_i + \zeta_t + \theta_{it} + \gamma_{1(j_1)} + \lambda\omega_{(j_2)} + \gamma_{2(j_2)} + \gamma_{3(j_3)} \quad (4-2)$$

#### 4.6.1. Variance partition coefficients

Variance partition coefficients (VPCs) quantify the degree to which the residual spatiotemporal variation of violent crime is explained by each set of random effects parameters in Model 4–1 and Model 4–2 (Goldstein et al. 2002). The VPC calculating the proportion of variation explained by the lower-level random effects parameters, for example, is equal to the sum of the empirical variances of  $u_i$  and  $\theta_{it}$  divided by the sum of the empirical variances of  $u_i$ ,  $\zeta_t$ ,  $\theta_{it}$ ,  $\gamma_{1(j_1)}$ ,  $\gamma_{2(j_2)}$ , and  $\gamma_{3(j_3)}$ . Similarly,

the VPC calculating the proportion of variation explained by the higher-level units is equal to the sum of the empirical variances of  $\gamma_{1(j_1)}$ ,  $\gamma_{2(j_2)}$ , and  $\gamma_{3(j_3)}$  divided by the sum of the empirical variances of  $u_i$ ,  $\zeta_t$ ,  $\theta_{it}$ ,  $\gamma_{1(j_1)}$ ,  $\gamma_{2(j_2)}$ , and  $\gamma_{3(j_3)}$  (Browne et al. 2001). For policy, it is also relevant to quantify the proportion of variation that is purely spatial (or stable over time), purely temporal (or stable over the study region), and spatiotemporal (or varies both in space and time). For example, if most of the variation of crime is spatial, then crime prevention initiatives may look to modify permanent geographical risk factors, but if the variation of crime is spatiotemporal, then policies and programs may look to target specific small-areas with increasing violent crime (Johnson et al., 2008; Quick et al., 2017). The VPC calculating the proportion of variation that is purely spatial, for example, is equal to the sum of the empirical variances of  $u_i$ ,  $\gamma_{1(j_1)}$ ,  $\gamma_{2(j_2)}$ , and  $\gamma_{3(j_3)}$  divided by the sum of the empirical variances of  $u_i$ ,  $\zeta_t$ ,  $\theta_{it}$ ,  $\gamma_{1(j_1)}$ ,  $\gamma_{2(j_2)}$ , and  $\gamma_{3(j_3)}$ .

#### 4.6.2. Prior distributions

In Bayesian modelling, all parameters are treated as random variables and are assigned prior probability distributions. The intercept ( $\alpha$ ) was assigned an improper uniform prior distribution and the regression coefficients ( $\beta$ 's,  $\kappa$ 's, and  $\lambda$ ) were assigned vague normal prior distributions with means of zero and variances of 1,000. The set of spatially unstructured random effects for DAs were assigned normal prior distributions with means of zero and a common unknown variance  $\sigma_u^2$ .

The random effects terms for neighbourhoods ( $\gamma_{1(j_1)}$ ), electoral wards ( $\gamma_{2(j_2)}$ ), and police zones ( $\gamma_{3(j_3)}$ ) were each assigned normal distributions with means of zero and common unknown variances  $\sigma_{\gamma_1}^2$ ,  $\sigma_{\gamma_2}^2$ , and  $\sigma_{\gamma_3}^2$ , respectively (Browne et al., 2001). Because the variance parameters for the higher-level random effects parameters were estimated from the data, these prior distributions do not assume that neighbourhoods, electoral wards, or police zones are relatively more or less important for explaining the spatiotemporal patterning of violent crime. These prior distributions also assume



that there is no spatial autocorrelation between the higher-level units. Preliminary models that included spatially structured random effects terms for the lower- and higher-level units (assigned intrinsic conditional autoregressive prior distributions as per Besag et al. (1991)) were tested but these parameters did not converge, did not improve model fit, and were not included in the final model.

The temporal terms ( $\zeta_t$ ) were assigned a normal distribution with means of ( $b_0 \cdot t^*$ ) and unknown variance  $\sigma_\zeta^2$ , where  $b_0$  is a regression coefficient and  $t^*$  is the mean-centred time ( $t^* = t - 3$ ) (Li et al., 2014). The regression coefficient  $b_0$  was assigned a vague normal prior distribution. This parameterization estimates a linear violent crime trend over the five years via ( $b_0 \cdot t^*$ ) and allows for the overall time trend ( $\zeta_t$ ) to depart from the linear trend for each time period via the additional Gaussian noise modeled by  $\sigma_\zeta^2$ . The space-time random effects terms ( $\theta_{it}$ ) were assigned normal distributions with means of zero and a common unknown variance  $\sigma_\theta^2$ . This prior distribution assumes that the residual space-time variability of crime is not correlated between small-areas or between years.

To complete the Bayesian hierarchical model, prior distributions were assigned to the variance parameters of the random effects terms. The standard deviation of each set of random effects terms ( $\sigma_u$ ,  $\sigma_{\gamma_1}$ ,  $\sigma_{\gamma_2}$ ,  $\sigma_{\gamma_3}$ ,  $\sigma_\zeta$ , and  $\sigma_\theta$ ) was assigned a positive half-Gaussian prior distribution,  $\text{Normal}_{+\infty}(0, 10)$  (Gelman, 2006). To test for the sensitivity of model results to the prior distributions of the random effects parameters, two alternative prior distributions were specified for the precisions of all random effects parameters, *Inverse Gamma*(0.001, 0.001) and *Inverse Gamma*(0.5, 0.0005) (Kelsall and Wakefield, 1999; Browne et al., 2001). The results of these sensitivity analyses were nearly identical to the results shown here.

### **4.6.3. Model fitting**

Model 4–1 and Model 4–2 were fitted using the Markov chain Monte Carlo algorithm (MCMC) in WinBUGS v.1.4.3. The WinBUGS code for Model 4–2 is shown in Appendix K. Two MCMC chains were initiated at dispersed initial values and the first 200,000 iterations (for each chain) were discarded as burn-in. Convergence of model parameters was monitored via visual inspection of trace plots and via Brooks-Gelman-Rubin diagnostics. For inference, an additional 200,000 iterations were sampled for each MCMC chain, retaining every twentieth iteration to reduce autocorrelation of the posterior samples. The Monte Carlo errors for all model parameters were less than five percent of the corresponding posterior standard deviations, indicating that the total number of iterations were sufficient to approximate the posterior distributions (Lunn et al. 2012). The Deviance Information Criterion (DIC) was used to compare Model 4–1 and Model 4–2. The DIC balances goodness of fit and model complexity, where goodness of fit is assessed via the posterior mean deviance and model complexity is assessed via the effective number of parameters (Spiegelhalter et al., 2002). The model with the smallest DIC value is considered to be the best-fitting model.

### **4.7. Results**

The DIC values for Model 4–1 and Model 4–2 are shown in Table 4.1. Model 4–2 had a smaller DIC value than Model 4–1. This provides evidence that model fit improved when accounting for the clustering of violent crime within neighbourhoods, electoral wards, and patrol zones. The posterior medians and 95% credible intervals (95% CI) of the intercept, the regression coefficients, and the variance parameters of the random effects terms from Model 4–1 and Model 4–2 are also shown in Table 4.1. The 95% CI is the interval that contains the true value of a parameter with 95% probability. The regression coefficients are interpreted as relative risks (i.e., exponential transformations of  $\beta$ 's,

$\kappa$ 's, and  $\lambda$ ), where coefficient values greater than one indicate positive associations between the explanatory variables and violent crime<sup>5</sup>.

**Table 4.1. Model fit criterion and posterior medians and 95% uncertainty intervals (in parentheses) for parameters in Model 4–1 and Model 4–2.**

	Model 4–1	Model 4–2
Deviance Information Criterion (DIC)	8,901	8,895
Intercept ( $\exp(\alpha)$ )	0.76 (0.68, 0.85)	0.83 (0.70, 1.01)
Population	1.28 (1.20, 1.38)	1.25 (1.17, 1.34)
Central business district	3.34 (2.16, 5.21)	3.31 (2.07, 5.25)
Residential instability	1.15 (0.98, 1.35)	1.15 (0.97, 1.36)
Socioeconomic disadvantage	1.43 (1.08, 1.85)	1.30 (1.00, 1.70)
Family disruption	1.03 (0.82, 1.30)	1.04 (0.82, 1.34)
Ethnic heterogeneity	1.02 (0.92, 1.12)	1.05 (0.94, 1.17)
Percent of active voters	NA	0.88 (0.78, 0.98)
Empirical variances of lower-level random effects		
Spatial ( $u_i$ )	1.22 (1.10, 1.36)	1.07 (0.95, 1.22)
Space-time ( $\theta_{it}$ )	0.07 (0.04, 0.10)	0.07 (0.05, 0.10)
Empirical variance of higher-level random effects		
Neighbourhood ( $\gamma_1$ )	NA	0.11 (0.04, 0.22)
Electoral ward ( $\gamma_2$ )	NA	0.02 (0.00, 0.07)

<sup>5</sup> Following Congdon (2011), the regression coefficients were standardized in order to compare the relative effects of the observed explanatory variables and the latent factors (see Appendix I). Table 4.1 reports the posterior medians and uncertainty intervals from the standardized regression coefficients.

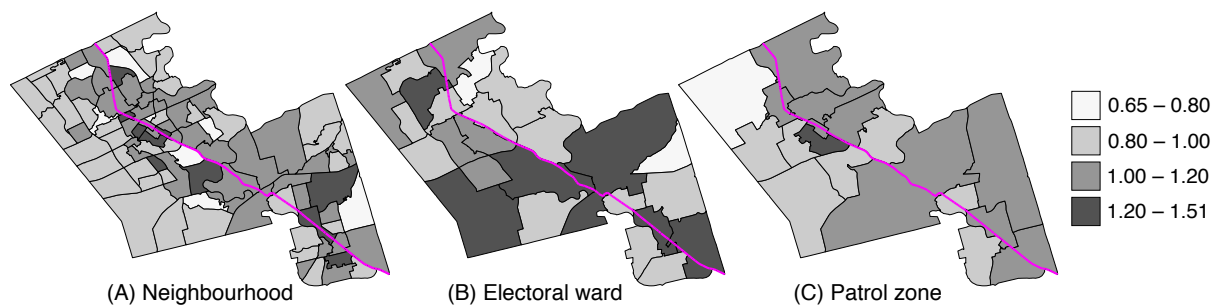
Patrol zones ( $\gamma_3$ )	NA	0.05 (0.01, 0.12)
Empirical variance of temporal effects ( $\zeta_t$ )	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)

Violent crime was found to be positively associated with population size, the central business district, and socioeconomic disadvantage within DAs. Broadly, these results support past research exploring the relationships between the urban environment and local crime patterns for a single spatial scale. From a social disorganization perspective, large population sizes are thought to increase the level of anonymity and distrust amongst residents and high levels of socioeconomic disadvantage have been shown to limit the formation of social ties and reduce resident-based informal social control (Sampson and Groves, 1989; Rosenfeld et al., 2001). From a routine activity perspective, areas with large populations likely have higher numbers of potential targets and offenders, and, consequently, more frequent opportunities for violent crime offenses. The central business district had the largest positive association with violent crime of all the covariates. In this study region, the central business districts have high densities of business-centred non-residential land uses and attract large numbers of residents and non-residents during routine activities. Combined, these attributes have been found to limit social interaction amongst residents and challenge the formation informal social control as well as facilitate frequent convergences between targets and offenders (Taylor, 1997).

Violent crime was also negatively associated with the percent of active voters at the electoral ward scale. In particular, the percent of active voters was found to have a contextual effect on violent crime such that small-areas located within higher voting electoral wards had, on average, lower violent crime than small-areas located within lower voting electoral wards, accounting for the lower-level sociodemographic and built environment covariates. This advances past studies that focus on the single-level relationships between civic engagement and crime by directly analyzing the effect of percent of active voters at the scale used by residents and communities to elect local representatives

and work with government to secure place-based resources (Weisburd et al., 2012; Rosenfeld et al., 2001). The relationship between the percent of active voters and violent crime is likely indirect insofar as it is an indicator of underlying public social control and collective efficacy that manifests through the relationships between residents, and the actions taken by residents, living in electoral wards.

Focusing on the higher-level units, Figure 4.3 maps the contextual effects of neighbourhoods, electoral wards, and patrol zones. Across the study region, neighbourhoods located close to the central commercial corridor generally had a positive influence on violent crime ( $\exp(\gamma_1) > 1$ ) and neighbourhoods around the periphery generally had a negative influence ( $\exp(\gamma_1) < 1$ ). Like neighbourhoods, electoral wards that had a negative influence on crime were typically located around the periphery of the study region, however, there was no clear grouping of high or low effects amongst electoral wards. For patrol zones, there was one area located close to the centre of the study region with a large positive effect on violent crime, however, the uncertainty intervals around the posterior medians of most patrol zone random effects terms included zero and so this spatial scale had no meaningful effect on violent crime. The heterogeneity of the higher-level effects reflects the ranking of the total empirical variances of the higher-level terms: neighbourhoods had the largest variance (0.11 with 95% CI: 0.04 – 0.22), electoral wards had the second largest variance (0.06 with 95% CI: 0.01 – 0.13), and patrol zones had the smallest variance (0.05 with 95% CI: 0.00 – 0.12). Note that most of the variance for electoral wards was due to the covariate for the percent of active voters (0.04 with 95% CI: 0.00 – 0.11) and that a relatively smaller proportion was due to the random effects terms (Table 4.1).



**Figure 4.3. Posterior medians of the higher-level neighbourhood ( $\exp(\gamma_1)$ ), electoral ward ( $\exp(\lambda\omega_{j_2} + \gamma_2)$ ), and police zone ( $\exp(\gamma_3)$ ) terms.**

Examining the VPCs for the random effects parameters in Model 4–1, the lower-level spatially unstructured random effects terms explained approximately 94% (95% CI: 91% – 96%) of the residual spatiotemporal variability of violent crime. Accounting for neighborhoods, electoral wards, and patrol zones in Model 4–2, this decreased to approximately 80% (95% CI: 71% – 87%). Combined, the three higher-level units explained about 14% (95% CI: 7% – 23%) of the total residual variability of violent crime, of which, neighbourhoods accounted for the largest proportion (8% with 95% CI: 3% – 15%). Patrol zone random effects terms captured about 4% (95% CI: 0.01% – 10%) and there was effectively no variance explained by the electoral ward random effects terms (1% with 95% CI: 0% – 6%). The VPCs for the space-time random effects (5% with 95% CI: 3% – 7%) and the time trend (1% with 95% CI: 0% – 2%) were consistent in both models. This broadly aligns with past multilevel analyses observing that the smallest geographical unit explains the greatest spatial variability of crime (Steenbeek and Weisburd, 2016; Schnell et al., 2017). The posterior medians and uncertainty intervals for the VPCs are shown in Appendix J.

#### 4.8. Discussion

This research has applied a Bayesian cross-classified multilevel modelling approach to analyze the multiscale spatiotemporal patterning of violent crime. Violent crimes were measured at the small-area scale (DAs) and small-areas were nested in neighbourhoods, electoral wards, and police patrol zones.

Violent crime was found to be positively associated with population size, the central business district, and socioeconomic disadvantage within DAs and negatively associated with the percent of active voters within electoral wards. Combined, the higher-level units explained approximately fourteen percent of the spatiotemporal variation of violent crime, of which, neighbourhoods were the most important source of variability. The cross-classified model used in this study accommodates multiple non-hierarchical higher-level units that each influence where and when crime events occur. The variation jointly attributed to the three overlapping higher-level units would otherwise be overlooked in single-level analyses or misattributed to one of the scales included in multilevel analyses of purely hierarchical data (Moerbeek, 2004; Leckie, 2013).

Examining spatiotemporal crime patterns via cross-classified multilevel models advances theoretical understanding of the multiscale processes influencing crime and provides area-specific information for crime prevention policy. Focusing first on the theoretical contributions, this study found that DAs were the most important set of geographical units for explaining where and when violent crime occurred. This suggests that the local contexts surrounding crime events have a greater impact than the broader social, political, and built environment contexts. Generally, the lower-level regression coefficients that were found to be associated with violent crime follow past research positing that small-area spatial units are more suitable than large areas for capturing variation in routine activity patterns, or the convergences between offenders and targets around specific activity nodes and activity pathways (Brantingham and Brantingham, 1993), as well as the variations of parochial social control, or the type of social control that arises from the non-intimate relationships amongst community members (Wooldredge, 2002).

Amongst the three higher-level units, neighbourhoods were the largest source of variation after accounting for social disorganization, routine activity, and collective efficacy covariates. The importance of neighbourhoods for explaining violent crime patterns can be interpreted from analytical and theoretical perspectives. Analytically, neighbourhoods were composed of fewer DAs than

electoral wards and patrol zones, and, as such, the DAs in a given neighbourhood were more likely to have similar levels of violent crime than the DAs nested in a given electoral ward or patrol zone.

Theoretically, neighbourhoods in the study region are created by local planning departments and are meaningful spatial units for capturing similarities in routine activity patterns and variations in public social control. For example, many of the peripheral neighbourhoods that were found to have a negative effect on violent crime are suburban and characterized by residential and open space land uses (Figure 4.3). These neighbourhoods are less likely to attract potential offenders and have frequent convergences between offenders and victims compared to neighbourhoods with many activity nodes, such as those that were found to have a positive effect on violent crime located close to the central commercial corridor (Greenberg et al., 1982). Likewise, because neighbourhoods generally align with the boundaries of neighbourhood associations and are used by local governments to allocate funding and resources for amenities and infrastructure, neighbourhoods are spatial units suitable for representing the relationships between community members as well as the relationships between neighbourhoods and extra-local organizations. Accordingly, a second explanation for the variation in neighbourhood-scale effects is that this pattern reflects the differing relationships between neighbourhoods and government, and specifically the degree to which neighbourhoods mobilize to secure common good resources and influence the political processes that shape neighbourhood environments (Velez, 2001; Kubrin and Weitzer, 2003)

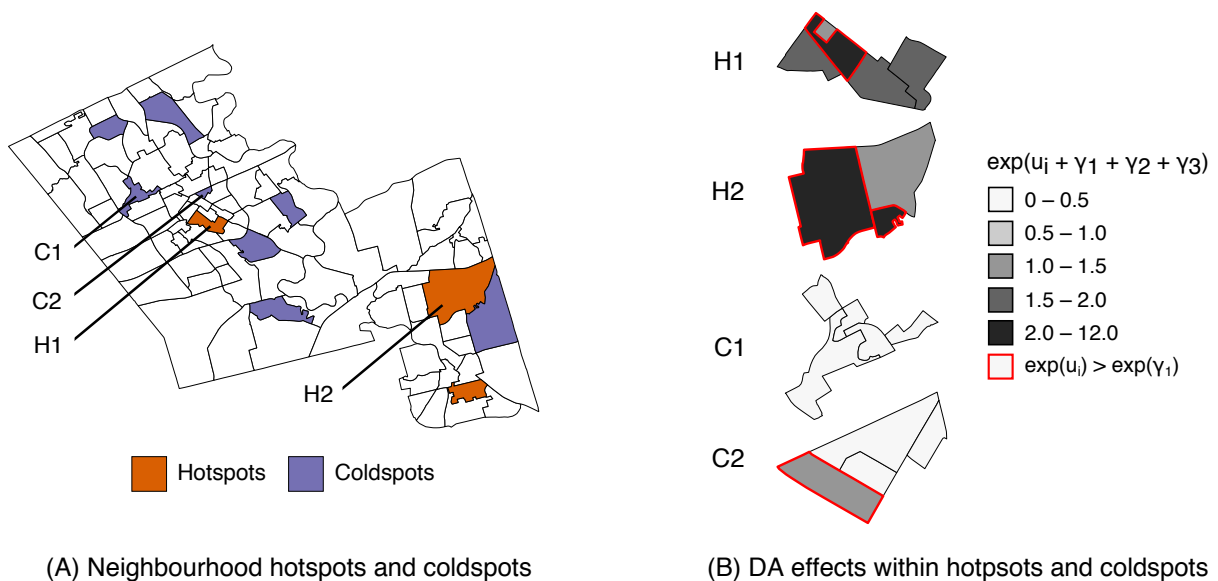
Electoral wards and patrol zones were found to explain the smallest proportions of the variation of violent crime amongst all four spatial scales (Appendix J). That is, after accounting for the relationship between high civic engagement and low violent crime within electoral wards, the results of this study show that these two higher-level areas were generally composed of DAs with a mix of high and low violent crime and that any additional crime-generating processes operating within electoral wards and patrol zones did not have a substantial influence on crime.



#### 4.8.1. Policy applications of multiscale crime patterns

Analyzing the spatiotemporal patterning of crime via a cross-classified multilevel modelling approach also provides information regarding the location, the scale, and the spatial/spatiotemporal focus of crime prevention policies. Based on the regression coefficients and the VPCs, this study indicates that policies and programs for violent crime should be designed areas located in and around the central business districts that are characterized by large populations, high levels of socioeconomic disadvantage, and low civic engagement at the DA and neighbourhood scales. Moreover, because the geographical variation of crime between areas was relatively consistent over time, crime prevention initiatives should focus on the underlying spatial pattern of violent crime rather than spatiotemporal variations within lower- or higher-level units. For reference, the spatial random effects terms for all four scales accounted for 94% (95% CI: 91% – 97%) of the total spatiotemporal variation of violent crime in Model 4–2 (see Section 4.5.1).

Focusing specifically on the interactions between DAs and neighbourhoods, Figure 4.4A identifies neighbourhood-scale violent crime hotspots and coldspots and Figure 4.4B details the DA-specific violent crime in two neighbourhood hotspots and two coldspots. Hotspots and coldspots had a strong positive or negative contextual effect on violent crime and were identified using the posterior probability of the neighbourhood random effects terms;  $\Pr(\exp(\gamma_1) > 1 \mid \text{data}) > 0.8$  for hotspots and  $\Pr(\exp(\gamma_1) < 1 \mid \text{data}) > 0.8$  for coldspots (Richardson et al., 2004). Broadly, Figure 4.4 shows that the neighbourhoods with a strong influence were more likely to have low crime than high crime (eight coldspots compared to three hotspots), that neighbourhood hotspots and coldspots were dispersed throughout the study region, and that DA-specific violent crime varied considerably within neighbourhoods.



**Figure 4.4. Neighbourhood hotspots and coldspots (A) and total DA violent crime within two hotspots and two coldspots (B). DAs with red boundaries had DA effects (posterior median of  $\exp(u_i)$ ) that were greater than neighbourhood effects (posterior median of  $\exp(\gamma_3)$ ). The insets of H1, H2, C1, and C2 are not to scale.**

For neighbourhood hotspots, urban planners may look to increase public social control by facilitating relationships between residents and local government, and by providing resources that can be used to address community-oriented projects. Urban planners are also well-positioned to modify the built environment of both neighbourhood hotspots and high crime DAs within neighbourhoods via land use zoning or urban design initiatives that increase perceptions of guardianship and reduce the likelihood that crime opportunities result in a crime offense (Johnson et al., 2008). Both of these strategies are primarily spatial insofar as public social control and the built environment are relatively stable over time. For DAs located within neighbourhood hotspots, and particularly for those with violent crime that exceeds the neighbourhood average, police may look to implement geographically-focused initiatives such as hotspot policing (Braga et al., 2014). While policing interventions likely occur over a relatively short period of time, past studies have shown that crime reduction benefits can diffuse from targeted areas to nearby areas and influence the stable spatial pattern of crime as well as temporal fluctuations (Guerette and Bowers, 2009).

#### **4.8.2. Limitations and future research**

One limitation of this research is that reported incident data was used to measure violent crime. While this type of data is common in past spatiotemporal analyses, and while the data used in this study includes only incidents with a filed police report, it is possible that victim or geographical characteristics influence the degree to which crime is reported to police and/or that reported crime types and locations were misclassified (Baumer, 2002; Klinger and Bridges, 1997). A second limitation is that covariates were not available and were not included for neighbourhoods and patrol zones. One reason for the lack of neighbourhood data may be that this set of spatial units are under the jurisdiction of three separate municipalities and each municipality has a distinct data collection and dissemination approach. Future work should look to add higher-level covariates that operationalize public social control, collective efficacy, and the distribution of police resources to directly quantify the processes influencing crime across multiple scales. Note that the modeling approach used in this study allows these higher-level covariates to vary over space and/or over time (Wheeler and Waller, 2008; Congdon, 2003). A third limitation of this study is the modifiable areal unit problem, which highlights the influence of spatial scale and zonal boundaries on the analysis of aggregate data (Openshaw, 1984). As such, this research should be taken in the context of the four spatial scales analyzed and alternative operationalizations of lower- and higher-level units should be investigated (Ratcliffe and McCullagh, 1999).

Future research should also explore how the multiscale patterns of multiple crime types are similar and different. Past research has suggested that many crime types are correlated and may be associated with the same underlying spatial risk factors, yet no study has examined how multiple crime types are correlated across multiple scales (Quick et al., 2018b; Yin et al., 2014). The cross-classified multilevel model used in this research can be extended to accommodate multiple outcomes and quantify the degree to which crime-general and crime-specific patterns are explained by each

spatial scale. Future work should also apply multilevel models to examine how specific crime, offender, or victim locations are influenced by small-area characteristics as well as multiple overlapping larger areas, while accounting for the correlation structure between points (i.e., via point process models) as well as higher-level areas (Rogerson and Sun, 2001; Diggle et al., 2013). Finally, multilevel cross-classified models should be applied to evaluate the impacts of crime prevention initiatives because they can incorporate the multiple overlapping areas used for hotspot policing and/or planning interventions, quantify the impact of policy implementation over time, and account for covariates at all scales.

## Chapter 5: Conclusion

### 5.1. Key findings

This dissertation is composed of three original research articles that explore the connections between crime and disorder, the urban environment, and urban planning in the Region of Waterloo, Ontario, Canada. The first article, titled *Spatiotemporal modelling of correlated small-area outcomes: Analyzing the shared and type-specific patterns of crime and disorder*, examined if, and how, physical disorder, social disorder, property crime, and violent crime shared a common spatial pattern and a common time trend (see Chapter 2). Three multivariate models with various assumptions regarding the correlation structures between these four outcomes were compared and the results of best-fitting model showed that all types of crime and disorder shared a common spatial pattern and a common time trend after accounting for local sociodemographic and built environment characteristics. The shared spatial component was found to explain the largest proportion of variation for all types of crime and disorder. Areas with high risk due to the shared spatial pattern were concentrated around the central commercial corridor. The results of this article also indicated that areas that transitioned from being type-specific disorder hotspots to type-specific crime hotspots were relatively infrequent in the study region.

The second article, titled *Time-varying relationships between land use and crime: A spatiotemporal analysis of small-area seasonal property crime trends*, quantified how the relationships between property crime and local land use changed over twelve seasons (see Chapter 3). The best-fitting spatiotemporal model featured two recurring time-varying covariates (for parks and eating and drinking establishments), four inconsistent time-varying covariates (for the additional land use types), and two time-constant covariates (for the sociodemographic characteristics). This study found that parks were more positively associated with property crime during spring/summer and that eating and drinking establishments were more positively associated during autumn/winter. The land

uses with recurring and inconsistent relationships with property crime were discussed in the context of obligatory time-constant and discretionary time-varying routine activities. Contrasting the variance partition coefficients for four spatiotemporal models with different time-constant and/or time-varying regression coefficients indicated that land use was relatively more important for explaining the spatial, rather than the temporal or spatiotemporal, patterning of property crime.

The third article, titled *Multiscale spatiotemporal patterns of crime: A Bayesian cross-classified multilevel modelling approach*, analyzed the spatiotemporal patterning of violent crime across four spatial scales (see Chapter 4). Crime data was measured at the small-area scale and small-areas were nested within planning neighbourhoods, electoral wards, and police patrol zones. The higher-level units (neighbourhoods, wards, and zones) were non-hierarchical and had overlapping geographical boundaries. At the small-area scale, violent crime was found to be associated with population size, the central business district, and socioeconomic disadvantage, and, at the electoral ward scale, violent crime was negatively associated with the percent of active voters. The three higher-level spatial units were found to explain approximately fifteen percent of the total spatiotemporal variation of violent crime, of which, planning neighbourhoods were the largest source of variability. Mapping the higher-level random effects terms showed that neighbourhoods close to the central commercial corridor and patrol zones close to the central business district in the city of Kitchener, Ontario, had the largest positive effects on violent crime.

## **5.2. Summarizing the research objectives and contributions**

As described in Section 1.3, this dissertation had theoretical, analytical, and policy-oriented research objectives. From a theoretical perspective, this dissertation sought to advance understanding of the relationships between crime, disorder, and the urban environment. From an analytical perspective, this dissertation was motivated to develop and apply novel statistical methods for analyzing crime, disorder, and urban environment data at the small-area scale. From a policy perspective, this

dissertation looked to provide information that could help the design and implementation of place-based crime prevention policies and programs in planning, local government, and law enforcement. The contributions of this dissertation to each objective are discussed below.

### **5.2.1. Theoretical contributions**

As a whole, this dissertation contributed to theory focused on the relationships between the urban environment and crime in two ways. First, this work identified local social, economic, demographic, built environment, and political characteristics that were associated with the local patterning of crime and disorder. Second, this dissertation examined the degree to which the data-generating processes associated with crime and disorder patterns were stable over space, stable over time, or dynamic in space-time. In general, this dissertation found that crime and disorder were positively associated with population size, residential instability, and the central business district, and that spatiotemporal crime and disorder patterns were relatively stable over time. By directly measuring why, and how, crime patterns vary over both space and time, this dissertation advances past research that investigates ecological crime theories for cross-sectional data and provides evidence suggesting that the mechanisms highlighted by both neighbourhood effects theories and opportunity theories are durable over time.

Each of the three research articles also make unique theoretical contributions. The first research article advanced collective efficacy theory by showing that physical disorder, social disorder, property crime, and violent crime were associated with the same observed and latent data-generating processes, as represented by the explanatory variables and the shared components, respectively. This challenges past studies that assume each crime type is explained by a unique data-generating process (Weisburd et al., 1993; Haberman, 2017) and supports work that hypothesizes that crime and disorder are associated with the same underlying spatial and temporal processes (Sampson and Raudenbush, 1993). The second research article extended routine activity theory and crime pattern theory by

making explicit the connections between different types of spatiotemporal activity patterns (obligatory activities and discretionary activities), local land use composition, and seasonal crime trends. Specifically, the research presented in Chapter 3 advances past studies that observe changing crime patterns but do not identify which built environment characteristics drive local seasonal increases or decreases in crime. The third research article articulated and operationalized a multiscale integration of routine activity theory, social disorganization theory (systemic model), and collective efficacy theory. This builds on past studies that focus on only one spatial scale and overlook how multiple geographical contexts simultaneously influence local crime risk.

### **5.2.2. Analytical contributions**

This dissertation has developed, applied, and disseminated a set of statistical models that provide a framework for analyzing the relationships between the urban environment and spatiotemporal crime patterns at the small-area scale. A Bayesian hierarchical modelling approach was used in all three research articles to partition the small-area spatiotemporal crime and/or disorder counts into a set of observed covariates and one or more sets of spatial random effects, temporal random effects, and space-time random effects (Knorr-Held and Besag, 1988; Knorr-Held 2000). Compared to testing-based methods, which are the most common types of methods used to explore spatiotemporal crime patterns, this Bayesian modeling approach strengthens inference of complex spatiotemporal data by directly modeling the observed and latent data-generating processes associated with crime and disorder (see Section 2.3).

The Bayesian hierarchical modeling approach used for this dissertation is flexible and can be modified to directly test specific research questions, as illustrated in the three research articles. In Chapter 2, multiple dependent variables were included and the underlying spatial and temporal correlation structures were modeled via two shared components. This extends existing work that compares and contrasts the results of separate cluster identification techniques or separate regression



models applied to a single crime type (see Section 2.3). In Chapter 3, a number of time-varying regression coefficient structures were specified in order to estimate the seasonal relationships with between local land use and property crime. Compared to studies that visually compare local seasonal crime patterns, this study provides an analytical framework for directly modeling how the associations between local characteristics and crime change over time. In Chapter 4, a cross-classified multilevel model was developed to account for the effects of multiple non-hierarchical higher-level units on small-area crime patterns, where each of the three higher-level units was informed by theory and/or policy. This work addresses the methodological limitations in past studies that analyze perfectly nested multilevel data or that analyze spatial scales separately.

### **5.2.3. Policy contributions**

In addition to advancing theories and methods focused on understanding of the relationships between crime and the urban environment, this dissertation provided evidence for crime prevention policies and programs in the Region of Waterloo, Ontario, Canada. Collectively, the three research articles in this dissertation provided two contributions to crime prevention. First, this dissertation found that areas with high physical disorder, social disorder, property crime, and violent crime had large population sizes, high levels of residential instability, and high levels of socioeconomic disadvantage. High crime and disorder areas were also located in the central business districts in the cities of Cambridge, Kitchener, and Waterloo. Because all of these variables have been operationalized as indicators of low informal social control, policies and programs that work to strengthen the relationships between residents and establish a common set of values may be effective at crime reduction in these areas. One way that planning can address informal social control, in particular, is through planning processes that attract and engage diverse residents to address local issues of collective importance (Sampson et al., 1997; Rukus and Warner, 2013). Second, the results of this dissertation show that spatiotemporal crime patterns were relatively stable over time. Unlike dynamic

crime patterns that may be better addressed via intermittent increases in resources, urban planning has the policy tools necessary to modify the stable features of the built and sociodemographic environments through land use plans, zoning by-laws, and urban design guidelines (Johnson et al., 2008).

Focusing on the policy contributions of each research article, in Chapter 2, the importance of the spatial shared component for explaining the variation of physical disorder, social disorder, property crime, and violent crime suggests that crime prevention initiatives be designed for the underlying processes shared amongst all crime and disorder types. Specific areas where these initiatives may be targeted are visualized in Section 2.7. In Chapter 3, land use types are classified as to whether they exhibit a time-constant or time-varying relationship with seasonal property crime trends, which highlights where, and how, urban planning and law enforcement should work hand-in-hand to address time-constant and time-varying crime patterns, respectively. Specifically, cyclic police patrols may be directed to areas with parks during the spring/summer and to areas with eating and drinking establishments during the autumn/winter, while time-constant planning policies modifying the local environment should target areas with commercial land uses, schools, and high concentrations of public transit stations. In Chapter 4, planning neighbourhoods were found to be the most important higher-level unit for explaining the spatiotemporal variation of violent crime, which suggests that neighbourhoods are a suitable scale at which to design and implement crime prevention policy, specifically for the planning neighbourhood hotspots and the nested small-area hotspots mapped in Section 4.7.

### **5.3. Limitations**

There are three limitations to this dissertation as a whole. The specific limitations for each research article are discussed in Chapters 2, 3, and 4. The first limitation concerns the degree to which the WRPS call-for-service data were representative of crime and disorder in the study region. Despite the

advantages of call-for-service data compared to official crime data and victimization data (i.e., less likely to be influenced by police bias and victim recall, respectively; see Section 1.6), it is challenging to verify that the call-for-service dataset used in this dissertation, as well as call-for-service datasets more generally, capture all of the “real” crime and disorder events and only the “real” crime and disorder events. The WRPS dataset has a number of features that improve the likelihood that the data analyzed in this dissertation are closer to representing the “real” level of crime than other similar datasets. Specifically, this dataset includes a variable indicating whether or not a police report was filed, which suggests that the caller and/or the police considered the incident to be serious enough to file an official report. This dataset also includes a variable indicating the final call type, which implies that it is possible for the initial (reported) type to be different from the final type following police investigation. Descriptive analyses of the data suggest that trends in calls-for-service within the study region are comparable to trends in official crime statistics, as disseminated by the Uniform Crime Reporting survey (see Section 1.6.4). However, it is important to acknowledge that quantitative crime datasets capture a fraction of the “real” crime and disorder events, that violent crimes tend to be reported more frequently than non-violent crimes, and that call-for-service data have a number of limitations around data misclassification and duplicate incidents (Goudriaan et al., 2006; Tarling and Morris, 2010; see Section 1.6.2).

The second limitation, which also concerns the WRPS call-for-service dataset, is that the spatial information assigned to each call-for-service was offset from the final call location to the nearest street intersection. While the WRPS dataset did include a final call type location, which implies that there was a smaller chance of there being geographical misclassifications due to reporting or recording errors as the call-for-service location may have been updated in response to police follow-up, it is possible that the offset intersections were located in a different DA than the location of the event and/or the location of the caller (see Section 1.6.4). This was due to the aggregation of incident points to small-areas for analysis. Broadly, this phenomenon is captured by the modifiable

areal unit problem, which recognizes that when aggregating point data to geographical areas, both the shape and the scale of the areas influence the characteristics of the data and the results of data analysis (Openshaw, 1984). The results presented in this dissertation must therefore be taken in context of the geographical units analyzed and cannot be generalized spatial units that are smaller/larger or different shapes. Future research focused on modeling crime point data may help to address this limitation (see Section 5.4.1).

The third limitation of this dissertation is that the spatiotemporal extent of the data, and the spatiotemporal extent of the three research articles, was the Region of Waterloo, Ontario, for a five-year time period from 2011 to 2015. This challenges the external validity of this research because the results cannot be directly compared and contrasted with analyses completed for different study regions in Ontario, Canada, or North America, or for different study periods prior to 2011 or after 2015. This limitation applies to most studies focusing on local spatial and spatiotemporal crime patterns because call-for-service data, which is the most common type crime and disorder data used at a small-area scale, is often collected and distributed by municipal and/or regional police services that each have a different approach to data cleaning, handling, and dissemination. One way to address this limitation would be for police associations or provincial or national governments to prescribe policies that mandate the processes involved in collecting, recording, validating, and distributing call-for-service data, or other types of crime data, with detailed spatial and temporal information.

#### **5.4. Future research**

Building on the theoretical, analytical, and policy contributions of this dissertation, future research exploring the relationships between spatiotemporal crime patterns and the urban environment should focus on developing statistical methods for point-based crime data and apply these methods, as well as spatiotemporal methods for small-area data, to investigate how crime and disorder are associated

with place-based land use and population changes, personal attributes and individual activity patterns, and place-based crime prevention interventions.

#### **5.4.1. Point-based research**

Motivated by research showing that crime opportunities and offenses concentrate at specific locations within the urban environment, contemporary spatial and spatiotemporal studies are increasingly focusing on analyzing data for micro-places, such as addresses and street segments (Weisburd et al., 2012). Compared to small-area crime data, address and street segment data may be better conceptualized as points that arise from a continuous spatial process rather than crime counts or rates that arise from a discrete spatial process that occurs only within small-areas and between adjacent small-areas (Cressie, 1991; Gelfand et al., 2010). As such, future studies should look to explore how spatial and spatiotemporal point process models can be applied to advance understanding of local crime and disorder patterns. In general, existing studies analyzing point-based crime data have used descriptive methods to visualize crime patterns and crime hotspots (e.g., kernel density estimation) but do not model the data-generating processes associated with point patterns (Ratcliffe and McCullagh, 1999; Anselin, 2000; Rogerson and Sun, 2001). Examples of (marked) point process models applied to crime data include Mohler et al. (2011) on self-exciting point processes to model space-time crime clustering, Mohler (2014) on homicide and gun crime prediction, and Taddy (2012) on weekly spatiotemporal violent crime patterns. One type of point process model that may be suitable for analyzing crime data is the log-Gaussian Cox process, which models counts of crime located at specific locations as a function of covariates and a spatially continuous process (Moller et al., 1998; Diggle et al., 2013). In the context of this dissertation, applying point process models to intersection data would address some of the limitations that arise when aggregation point data to areas (Section 5.3), however researchers should carefully consider how to integrate area-level covariates, such as census data, into these types point process models.

#### **5.4.2. Place-based research**

Future place-based research should focus on how crime and disorder patterns vary in response to spatial and temporal changes in land use and population characteristics. In this dissertation, all sociodemographic and built environment data were treated as constant because there were little available data measuring how local contexts changed over time, and because the data that were available showed little evidence of land use or population change across the five-year study period (e.g., NAICS measuring changes in specific land use types and 2011 and 2016 census data). Future studies examining crime over longer time periods may consider how crime increases or decreases in response to local land use changes, such as the increasing numbers of alcohol outlets and restaurants that accompany gentrification and associated processes of neighbourhood upgrading, or in response to local population changes, such as the increasing concentration of low-income households in suburban areas as driven by the growing social-spatial inequalities observed in many large metropolitan regions (see Section 1.5.1). An additional direction for future place-based research is to apply space-varying coefficients to investigate if, and how, the relationships between crime and local characteristics change across a study region. This would provide insight into how different contexts shape the ways in which local characteristics influence crime. For example, it is possible that eating and drinking establishments have a different association with property crime in suburban areas, in the central business district, and in industrial areas. In the Bayesian statistical framework, space-varying covariates are typically composed of an overall (or space-constant) component and a set of area-specific space-varying components (Assuncao, 2003; Gelfand et al., 2003). Geographically weighted regression (GWR) models accomplish a similar task in the frequentist statistical framework (Brunsdon et al., 1998; Fotheringham et al., 2003).

### **5.4.3. People-based research**

While this dissertation has focused on understanding how spatiotemporal patterns of crime and disorder are influenced by the urban environment, it is important to not overlook the role of individual characteristics, attitudes, and activity patterns. Routine activity theory and crime pattern theory both hypothesize that human activity patterns shape crime patterns, however most research employing these perspectives focus on the characteristics of places rather than people. As such, future people-based research should focus on measuring and analyzing the activity spaces of individuals, including crime offenders and non-offenders, to better understand how individual attributes interact with the urban environment and lead to criminal behaviour. One theoretical framework that specifically focuses on the complex interactions between individuals and the urban environment is situational action theory, which proposes that criminal behaviour is influenced by individual morals, individual decision-making processes, the interplay between these individual characteristics and features of the urban environment, and the broader social and life-history conditions that shape crime propensity (Wikstrom et al., 2009). Implicit in this theory are calls for new types of data that measure individual-level activity patterns – for a small cohort this may be accomplished via GPS monitoring or time-calendars, and at scale, potential data sources include mobile phones or social media (Reades, 2009; Hanaoka, 2016; Malleson and Andresen, 2015) – and analytical innovations that account for movement data and the changing exposures to environmental characteristics over time.

### **5.4.4. Policy-based research**

While spatiotemporal analyses can be used to identify where interventions and resources should be located and allocated, when interventions should occur, and what types of spatial, temporal, or spatiotemporal processes crime prevention interventions should be designed for, few studies evaluate the effects of crime prevention policies. Policy evaluation is most common in law enforcement, where research has shown that interventions such as hotspot policing, problem-oriented policing, or

increasing foot patrols reduce crime and disorder (Braga and Bond, 2008; Ratcliffe et al., 2011; Braga et al., 1999; Telep and Hibdon, 2018), however the impacts of crime prevention policies and programs as administered by urban planners and by local government are largely overlooked. Examples of planning-led interventions include lot greening programs (Branas et al., 2011; Branas et al., 2018; Sadler et al., 2017) and building ordinances that require operational doors and windows (Kondo et al., 2015). Across all policy domains, future research should pay particular attention to developing and applying more rigorous quantitative methods (Li et al., 2013; Kondo et al., 2018). For example, studies that employ interrupted time-series research designs with quasi-experimental data infrequently test their findings across many sets of control areas to ensure that the observed effects are robust across subsets of areas with similar locations and with similar socioeconomic and built environment characteristics.



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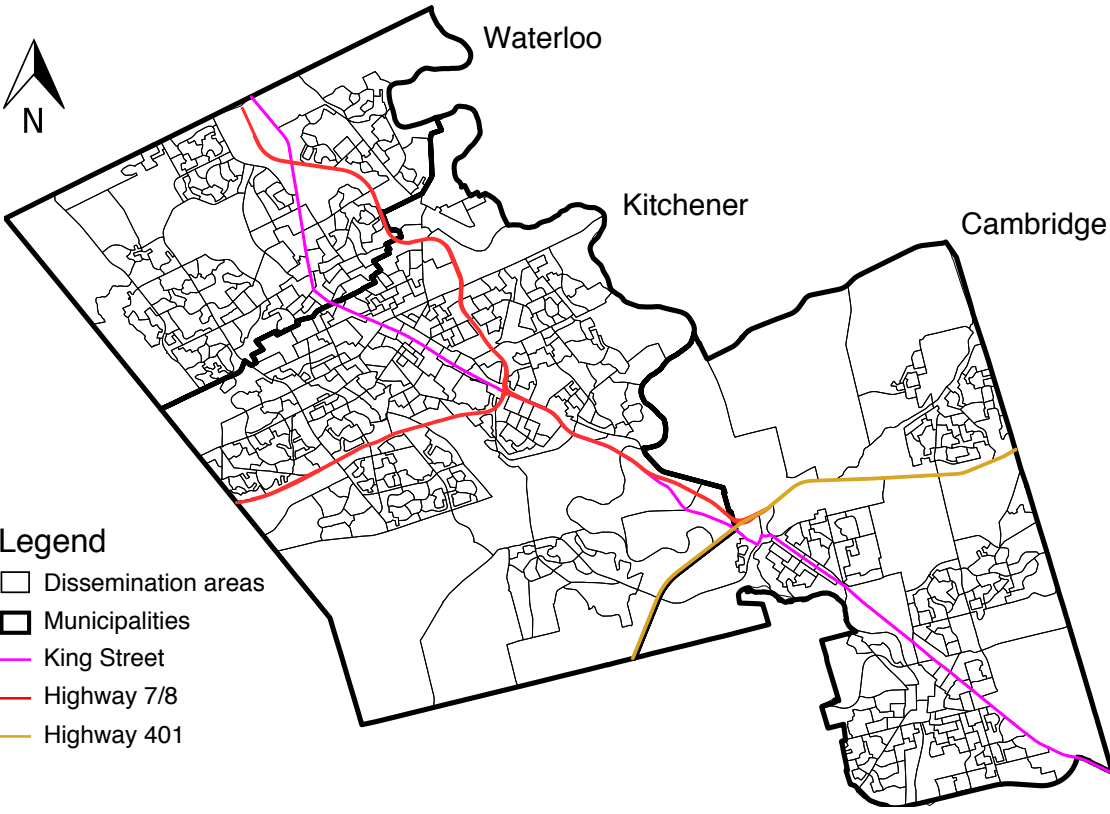
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**Appendix A: Detailed map of the study region**



## Appendix B: Supplementary descriptive statistics (Chapter 2)

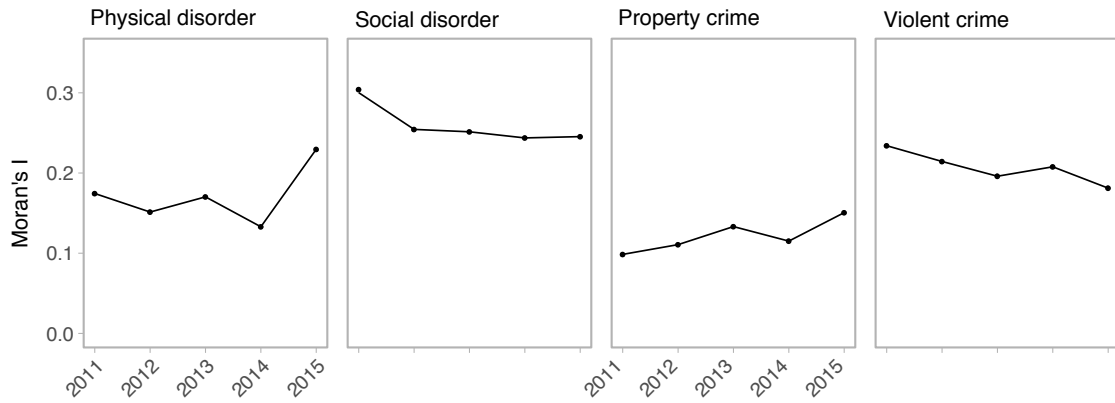


Figure B1. Annual Moran's I values for crime and disorder.

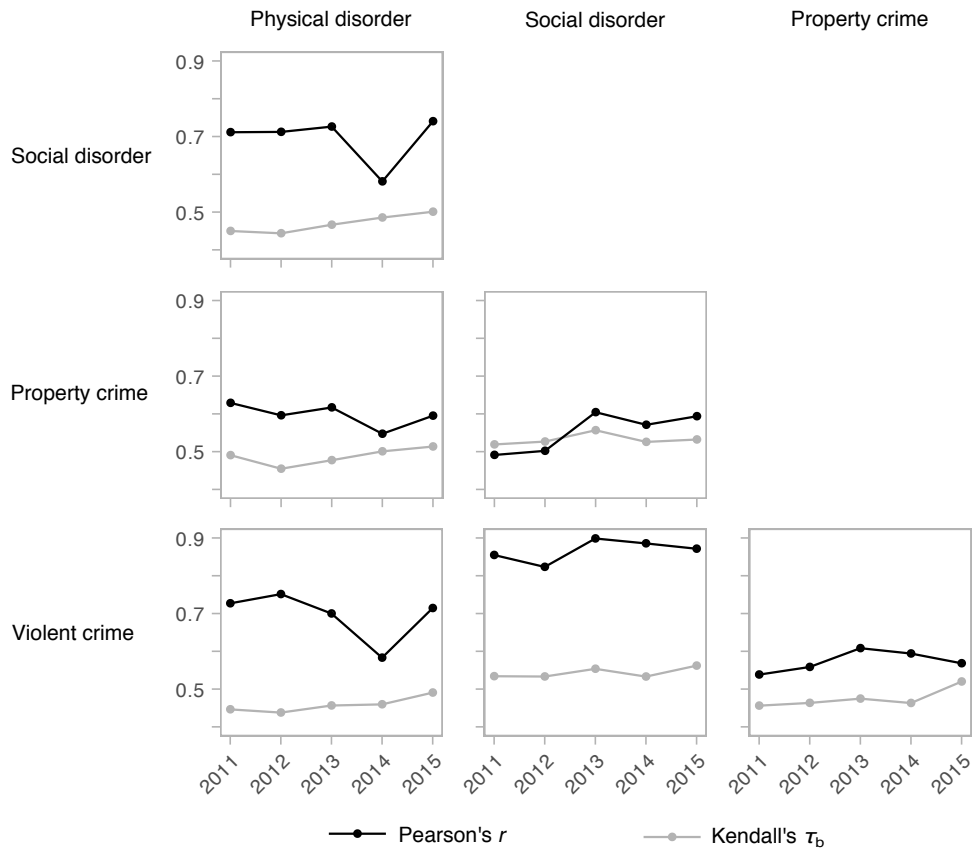
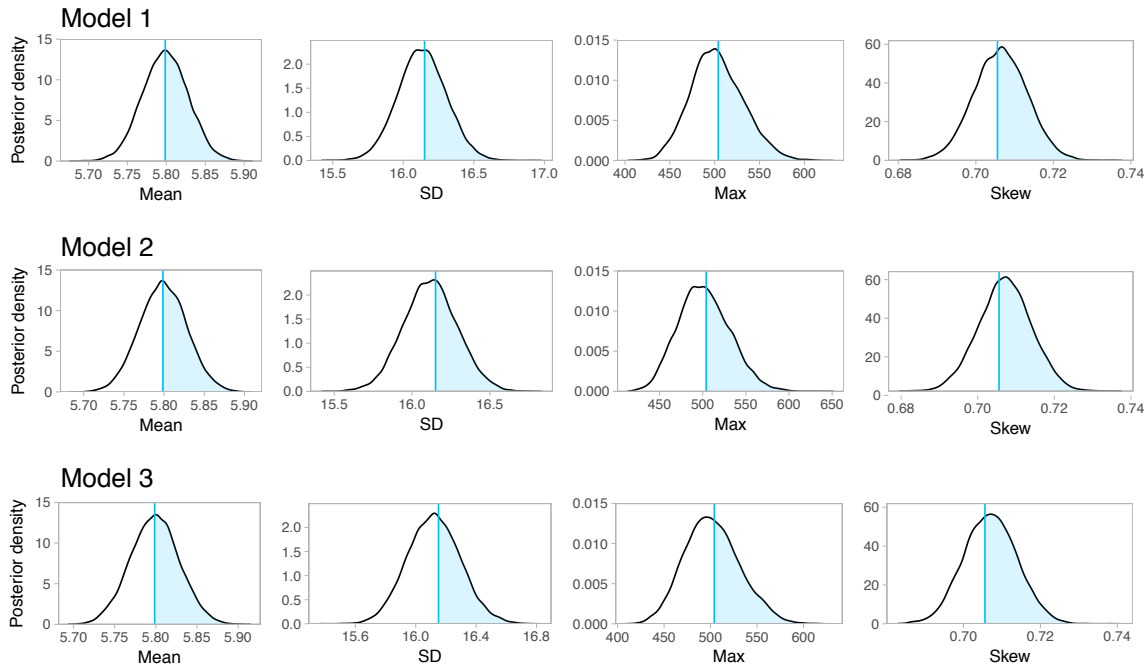


Figure B2. Annual pairwise correlation coefficients for crime and disorder counts.

## Appendix C: Posterior predictive distributions (Chapter 2)



**Figure C1.** Posterior predictive distributions for Models 2–1, 2–2, and 2–3. The shaded regions correspond to the posterior predictive p-values.

**Table C1.** Posterior predictive p-values for four test statistics from Models 2–1, 2–2, and 2–3.

	Mean	SD	Max	Skew
Model 2–1	0.50	0.46	0.46	0.55
Model 2–2	0.50	0.42	0.45	0.59
Model 2–3	0.50	0.43	0.46	0.58

## Appendix D: Variance partition coefficients (Chapter 2)

**Table D1. VPCs for Model 2–1. Posterior medians and 95% credible intervals are shown.**

	Physical disorder	Social disorder	Property crime	Violent crime
$s_{ik}$	83.46 (80.23, 86.46)	95.61 (93.84, 97.12)	90.74 (89.08, 92.29)	95.04 (92.88, 96.88)
$\gamma_{jk}$	3.00 (1.44, 4.63)	0.28 (0, 1.45)	1.08 (0, 2.26)	0.57 (0, 1.80)
$\theta_{ijk}$	13.50 (10.74, 16.53)	4.09 (2.56, 5.84)	8.17 (6.63, 9.73)	4.38 (2.59, 6.47)

**Table D2. VPCs for Model 2–2.**

	Physical disorder	Social disorder	Property crime	Violent crime
$s_{ik}$	11.76 (8.50, 14.94)	1.85 (0, 6.43)	19.27 (16.52, 22.28)	7.55 (4.62, 10.81)
$\gamma_{jk}$	2.49 (1.00, 4.00)	0.26 (0, 1.39)	0.97 (0, 2.16)	0.55 (0, 1.76)
$\theta_{ijk}$	11.40 (8.90, 14.20)	3.90 (2.36, 5.55)	7.44 (5.87, 9.01)	4.68 (2.70, 6.88)
$\lambda_k \cdot f_i$	74.33 (70.80, 77.83)	93.92 (89.45, 96.54)	72.30 (68.91, 75.40)	87.14 (83.91, 90.05)

**Table D3. VPCs for Model 2–3. Posterior medians and 95% credible intervals are shown.**

	Physical disorder	Social disorder	Property crime	Violent crime
$s_{ik}$	11.62 (8.43, 14.85)	2.05 (0.01, 6.40)	19.26 (16.48, 22.46)	7.50 (4.71, 10.84)
$\gamma_{jk}$	0.41 (0, 2.45)	0.10 (0, 1.76)	0.24 (0, 1.90)	0.06 (0, 1.49)
$\theta_{ijk}$	11.54 (8.95, 14.44)	3.96 (2.36, 5.57)	7.44 (5.88, 9.07)	4.76 (2.86, 6.91)

$\lambda_k \cdot f_i$	74.63 (70.51, 78.06)	93.13 (88.36, 95.91)	71.74 (67.34, 75.00)	86.81 (82.64, 89.87)
$\phi_k \cdot t_j$	1.45 (0, 4.71)	0.37 (0, 2.59)	1.08 (0, 4.06)	0.61 (0, 2.89)

## Appendix E: WinBUGS code for Model 2–3 (Chapter 2)

```

model {
for (i in 1:N){          ### N is areas
for (j in 1:J) {        ### J is time periods
for (k in 1:K) {        ### K is crime/disorder types

O[i,j,k] ~ dpois(mu[i,j,k])

### centered parameterization of log(mu[i,j,k])
log(mu[i,j,k]) <- log.mu[i,j,k]
log.mu[i,j,k] ~ dnorm(eta[i,j,k], tau.theta[k])
eta[i,j,k] <- alpha[k] + s[k,i] + gamma[k,j] + (lambda[k] * f[i]) + (phi[k] * t[j]) + (beta1[k] * popcount[i]) +
(beta2[k] * lowinc[i]) + (beta3[k] * mov[i]) + (beta4[k] * ieh[i]) + (beta5[k] * cbd[i])

### calculate space-time parameters (theta[i,j,k])
theta[i,j,k] <- log.mu[i,j,k] - eta[i,j,k]
}}

##### PARAMETERS #####
# alpha[k] = intercepts      s[k,i] = type-specific spatial random effects      beta[k]'s = coefficients

# gamma[k,j] = type-specific temporal random effects      lambda[k] = loading for spatial shared
component
# f[i] = shared spatial random effects      t[j] = shared temporal random effects
# phi[k] = loading for temporal shared component      theta[l,j,k] = spatiotemporal random effects
### shared time trend
for (k in 1:K){
  logphi[k] ~ dnorm(0, 5.9)
  logphi.c[k] <- logphi[k] - mean.phi
  phi[k] <- exp(logphi.c[k])
}
mean.phi <- mean(logphi[1:4])
for (p in 1:sumNumNeigh.t) { weights.t[p] <- 1 }      ### set weights for temporal ICAR
t[1:J] ~ car.normal(adj.t[], weights.t[], num.t[], 1)
for (j in 1:J) { exp.t[j] <- exp(t[j]) }

### shared spatial pattern
for (p in 1:sumNumNeigh.s) { weights.s[p] <- 1 }      ### set weights for spatial ICAR
f[1:N] ~ car.normal(adj.s[], weights.s[], num.s[], 1)
for (k in 1:K) { lambda[k] ~ dnorm(0, 0.001)|(0, ) }

### type-specific spatial patterns and time trends
for (k in 1:K) {
s[k, 1:N] ~ car.normal(adj.s[], weights.s[], num.s[], tau.s[k])
gamma[k, 1:J] ~ car.normal(adj.t[], weights.t[], num.t[], tau.gamma[k])
}

### set priors for intercepts, coefficients, and set hyperpriors for random effects terms
for (k in 1:K) {
  tau.theta[k] <- 1 / pow(sd.theta[k], 2); sd.theta[k] ~ dnorm(0, 10)|(0, )
  alpha[k] ~ dflat()
  beta1[k] ~ dnorm(0, 0.001); beta2[k] ~ dnorm(0, 0.001); beta3[k] ~ dnorm(0, 0.001)
}

```

```
beta4[k] ~ dnorm(0, 0.001); beta5[k] ~ dnorm(0, 0.001)
tau.s[k] <- 1 / pow(sd.s[k], 2); sd.s[k] ~ dnorm(0, 10)|(0,)
tau.gamma[k] <- 1 / pow(sd.gamma[k], 2); sd.gamma[k] ~ dnorm(0, 10)|(0,)
}}
```



## Appendix F: Variance partition coefficients (Chapter 3)

**Table F1. Posterior medians and 95% credible intervals (in parentheses) for the variance partition coefficients for observed explanatory variables and random effects in Models 3–1, 3–2, 3–3, and 3–4.**

Model	$u_i + s_i$	$\lambda_j$	$\phi_{ij}$	Sociodemographic characteristics	Land use characteristics
3–1	0.86 (0.84, 0.87)	0.05 (0.04, 0.06)	0.10 (0.08, 0.11)	NA	NA
3–2	0.62 (0.58, 0.65)	0.06 (0.05, 0.08)	0.11 (0.10, 0.13)	0.07 (0.04, 0.10)	0.15 (0.11, 0.18)
3–3	0.61 (0.57, 0.65)	0.08 (0.06, 0.09)	0.11 (0.09, 0.12)	0.07 (0.04, 0.09)	0.15 (0.11, 0.20)
3–4	0.62 (0.58, 0.65)	0.07 (0.05, 0.09)	0.11 (0.09, 0.13)	0.07 (0.04, 0.10)	0.14 (0.10, 0.18)

## Appendix G: WinBUGS code for Model 3–4 (Chapter 3)

```

model {
for (i in 1:N) {
for (t in 1:T) {
  O[i,t] ~ dpois(mu[i,t])

  ### hierarchical centering
  log(mu[i,t]) <- log.mu[i,t]
  log.mu[i,t] ~ dnorm(r[i,t], tau.r)

  ### model crime counts
  r[i,t] <- alpha + s[i] + u[i] + lambda[t] + timeconstant[i] + timevarying[i,]
  timeconstant[i,t] <- (kappa1 * pop[i]) + (kappa2 * mov5yr[i])
  timevarying[i,t] <- (psi3[t] * bia.bin[i]) + (psi4[t] * comm.bin[i]) + (psi[t] * eatdrink.bin[i]) +
(psi6[t] * park.bin[i]) + (psi7[t] * transit.den[i]) + (psi8[t] * school.bin[i])

  ### recover space-time random effects
  phi[i,t] <- log.mu[i,t] - r[i,t]
}
u[i] ~ dnorm(0, tau.u)
}

### set priors on random effects
alpha ~ dflat()
tau.r <- 1 / pow(sd.r, 2); sd.r ~ dnorm(0, 10)|(0, )
tau.u <- 1 / pow(sd.u, 2); sd.u ~ dnorm(0, 10)|(0, )
for (j in 1:sumNumNeigh.s) { weights.s[j] <- 1 }
s[1:N] ~ car.normal(adj.s[], weights.s[], num.s[], tau.s)
tau.s <- 1 / pow(sd.s, 2); sd.s ~ dnorm(0, 10)|(0, )
for (j in 1:sumNumNeigh.t) { weights.t[j] <- 1 }
lambda[1:T] ~ car.normal(adj.t[], weights.t[], num.t[], tau.lambda)
tau.lambda <- 1 / pow(sd.lambda, 2); sd.lambda ~ dnorm(0, 10)|(0, )

### set time-varying coefficients for two seasons // note the nested indexing
### year.index takes values 1 (for t = 1 to 4), 2 (for t = 5 to 8), 3 (for t = 9 to 12)
### season.index takes values 1 (for t = 1, 2), 2 (for t = 3, 4), 3 (for t = 5, 6), etc.
for (t in 1:T) {
psi3[t] <- beta3 + gamma3[t]
psi4[t] <- beta4 + gamma4[t]
psi5[t] <- beta5[year.index[t]] + gamma5[season.index[t]]
psi6[t] <- beta6[year.index[t]] + gamma6[season.index[t]]
psi7[t] <- beta7[year.index[t]] + gamma7[season.index[t]]
psi8[t] <- beta8 + gamma8[t]
}

### set baseline fixed effects
for (q in 1:3) {
  beta5[q] ~ dnorm(0, 0.0001)
  beta6[q] ~ dnorm(0, 0.0001)
  beta7[q] ~ dnorm(0, 0.0001)
}

```

```

}

kappa1 ~ dnorm(0, 0.0001); kappa2 ~ dnorm(0, 0.0001)
beta3 ~ dnorm(0, 0.0001); beta4 ~ dnorm(0, 0.0001); beta8 ~ dnorm(0, 0.0001)

### note: also tested gamma3 ~ dnorm(0, 0.0001) with similar results, e.g.
gamma3[1:T] ~ car.normal(adj.t[], weights.t[], num.t[], tau.gamma3)
gamma4[1:T] ~ car.normal(adj.t[], weights.t[], num.t[], tau.gamma4)
gamma8[1:T] ~ car.normal(adj.t[], weights.t[], num.t[], tau.gamma8)

### set sd's and corresponding precisions for timevarying random effects
tau.gamma3 <- 1 / pow(sd.gamma3, 2); sd.gamma3 ~ dnorm(0, 10)|(0, )
tau.gamma4 <- 1 / pow(sd.gamma4, 2); sd.gamma4 ~ dnorm(0, 10)|(0, )
tau.gamma8 <- 1 / pow(sd.gamma8, 2); sd.gamma8 ~ dnorm(0, 10)|(0, )

### set time-varying components for eating and drinking (spr/sum = 0, allow aut/wint to vary)
gamma5[1] <- 0; gamma5[3] <- 0; gamma5[5] <- 0
gamma5[2] ~ dnorm(0, 0.0001); gamma5[4] ~ dnorm(0, 0.0001); gamma5[6] ~ dnorm(0, 0.0001)

### set time-varying components for park (aut/wint = 0, allow spr/sum to vary)
gamma6[1] ~ dnorm(0, 0.0001); gamma6[3] ~ dnorm(0, 0.0001); gamma6[5] ~ dnorm(0, 0.0001)
gamma6[2] <- 0; gamma6[4] <- 0; gamma6[6] <- 0

### set time-varying components for public transit (spr/sum = 0, allow aut/wint to vary)
gamma7[1] <- 0; gamma7[3] <- 0; gamma7[5] <- 0
gamma7[2] ~ dnorm(0, 0.0001); gamma7[4] ~ dnorm(0, 0.0001); gamma7[6] ~ dnorm(0, 0.0001)
}

```

## Appendix H: Descriptive statistics (Chapter 4)

**Table H1. Total and annual violent crime counts at the DA scale.**

	Total count	Mean	SD	Min	Max
Total	6,813	10.39	21.22	0	335
2011	1,532	2.34	4.57	0	52
2012	1,436	2.19	4.51	0	63
2013	1,295	1.97	4.42	0	72
2014	1,230	1.88	4.43	0	72
2015	1,320	2.01	4.67	0	76

**Table H2. Descriptive statistics explanatory variables and the results of factor loadings.**

Posterior medians and 95% CIs of the factor loadings are shown.

	Mean	SD	Factor loading
Residential population	712.69	609.03	NA
Central business district	0.02	NA <sup>a</sup>	NA
Percent of voters (%)	26.49	6.48	NA
Residential instability			
Five-year residential mobility (%)	37.81	15.13	1.00
Renters (%)	30.72	27.11	0.74 (0.68, 0.80)
Socioeconomic disadvantage			
Median after-tax household income (\$)	69,819.31	23,528.13	-1.00
Low-income individuals (%)	8.05	8.20	0.67 (0.61, 0.74)
Unemployment rate (%)	6.83	3.84	0.38 (0.31, 0.46)
Government transfer payments (%)	12.44	5.59	0.78 (0.72, 0.84)
Family disruption			
Single parent families (%)	17.83	8.72	1.00 (0.91, 1.11)
Divorced or separated households (%)	9.33	4.43	1.00
Ethnic heterogeneity			
Index of ethnic heterogeneity (0 to 1)	0.34	0.15	1.03 (0.81, 1.33)
Index of language heterogeneity (0 to 1)	0.37	0.14	1.00

<sup>a</sup> Standard deviation not reported for binary variables.

## Appendix I: Bayesian factor analysis models (Chapter 4)

Let  $Y_{ik}$  denote the standardized rates of the ten explanatory variables associated with one of the four latent constructs, where  $i$  indexes small-areas ( $i = 1, \dots, 656$ ) and  $k$  indexes the variable type ( $k = 1, \dots, 10$ ).  $Y_{ik}$  were assumed to follow a normal distribution with mean  $\eta_{ik}$  and with an unknown variance for each variable  $\sigma_{\eta k}^2$ ;  $Y_{ik} \sim \text{Normal}(\eta_{ik}, \sigma_{\eta k}^2)$  (Congdon, 2011). Model I-1 estimates the four latent constructs representing residential instability, socioeconomic disadvantage, family disruption, and ethnic heterogeneity ( $n = 1, \dots, 4$ ). Each of the ten census variables was modeled as the sum of a type-specific intercept ( $\alpha_{\eta k}$ ) and a factor component ( $\lambda_{nk} \cdot \psi_{ni}$ ), where  $\lambda_{nk}$  are the factor loadings and  $\psi_{ni}$  are the area-specific estimates of the four latent constructs. Following past research, each variable was *a priori* assigned to the latent constructs (Sampson et al., 1997; Sutherland et al., 2013). For example,  $\lambda_{1,1}$  and  $\lambda_{1,2}$  represent the factor loadings for the percent of renters and the five-year mobility rate, respectively, and these variables were associated with the latent construct measuring residential instability,  $\psi_{1i}$  (see Appendix H and Section 4.4.1 for census variables and associated constructs).

$$\eta_{ik} = \alpha_{\eta k} + (\lambda_{nk} \cdot \psi_{ni}) \quad (\text{I-1})$$

The standard deviations of type-specific variance parameters ( $\sigma_{\eta k}$ ) were assigned positive half-normal prior distributions with means of zero and variances of 1,000 (Gelman, 2006). The type-specific intercepts ( $\alpha_{\eta k}$ ) were assigned improper uniform prior distributions. To ensure model identifiability, one factor loading from each construct was set to positive (or negative) one, specifically for percent of renters ( $\lambda_{1,1} = 1$ ), median household income ( $\lambda_{2,1} = -1$ ), separated/divorced families ( $\lambda_{3,1} = 1$ ), and the index of language heterogeneity ( $\lambda_{4,1} = 1$ ). The remaining factor loadings were assigned positive half-Gaussian prior distributions with means of zero and variances of 1,000 (Congdon, 2011). The four sets of random effects terms representing the latent variables were assigned a multivariate normal distribution with means set to zero and with a four-by-four variance-covariance matrix  $\Sigma$ . The multivariate normal distribution allows for correlation between the latent variables, where the diagonal elements of  $\Sigma$  are the conditional variances of the four sets of random effects and the off-diagonal elements are the covariances between the four constructs. The inverse of  $\Sigma$  was assigned a Wishart prior distribution with five degrees of freedom and diagonal and off-diagonal elements assigned values of 0.02 and 0, respectively (Thomas et al., 2004). Note that it is possible to impose spatial structure on the latent variables via a multivariate conditional autoregressive prior, as

illustrated by Congdon (2008) and Congdon (2011). Regression coefficients from analyses using spatially structured latent variables were virtually identical to the results shown in Table 4.1. Following Congdon (2011), the equations to standardize the regression coefficients for the observed explanatory variables and latent explanatory variables are shown in Models I-2, I-3, I-4, and I-5;  $\beta_1^{(s)}$  is the standardized regression coefficient for population size,  $\beta_2^{(s)}$  is the standardized regression coefficient for the central business district,  $\kappa_n^{(s)}$ 's are the standardized regression coefficients for the latent variables, and  $\lambda^{(s)}$  is the standardized regression coefficient for the percent of active voters. The standard deviations of the observed and latent explanatory variables are denoted by  $\sigma_{x_j}$  and  $\sigma_{\psi_n}$ , respectively, and  $\phi$  is the square root of the variance of the modeled violent crime counts ( $\phi = \text{var}(\log(\mu_{it}))^{0.5}$ ).

$$\beta_1^{(s)} = (\beta_1 \cdot \sigma_{x_1}) / \phi \quad (\text{I-2})$$

$$\beta_2^{(s)} = \beta_2 / \phi \quad (\text{I-3})$$

$$\kappa_n^{(s)} = (\kappa_n \cdot \sigma_{\psi_n}) / \phi \quad (\text{I-4})$$

$$\lambda^{(s)} = (\lambda \cdot \sigma_{\omega}) / \phi \quad (\text{I-5})$$

## Appendix J: Variance partition coefficients (Chapter 4)

**Table J1. Posterior medians and 95% CIs (in parentheses) of the VPCs for lower-level and higher-level random effects terms in Model 4–1 and Model 4–2.**

	Model 1	Model 2
Lower-level random effects terms	0.99 (0.98, 1.00)	0.85 (0.76, 0.93)
Spatial	0.94 (0.91, 0.96)	0.80 (0.72, 0.87)
Space-time	0.05 (0.03, 0.07)	0.05 (0.03, 0.07)
Higher-level random effects terms	NA	0.14 (0.07, 0.23)
Neighbourhood	NA	0.08 (0.03, 0.15)
Electoral ward	NA	0.01 (0.00, 0.06)
Patrol zone	NA	0.04 (0.01, 0.11)
Temporal effects	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)



## Appendix K: WinBUGS code for Model 4–2 (Chapter 4)

```

model{
for (i in 1:Narea_16) {
for (t in 1:T) {
  O[i,t] ~ dpois(mu[i,t])
  log(mu[i,t]) <- u[i] + zeta_model[t] + (beta[1] * pop[i]) + (beta[2] * cbd[i]) + (kappa[1] * instab[i])
  + (kappa[2] * disadv[i]) + (kappa[3] * family[i]) + (kappa[4] * heterog[i]) + theta[i,t] +
  gamma1[HOOD_ID[i]] + gamma2[WARD_ID[i]] + gamma3[ZONE_ID[i]] + (lambda *
  voters[WARD_ID[i]])
  theta[i,t] ~ dnorm(0, tau.r) # lower-level space-time random
  effects
}
}
for (p in 1:Nhood) { # neighbourhoods
  gamma1[p] ~ dnorm(0, tau.hood)
  hot_gamma1[p] <- step(exp(gamma1[p]) - 1) # neighbourhood hotspot
  cold_gamma1[p] <- step(-(exp(gamma1[p]) - 1)) # neighbourhood coldspot
}
tau.hood <- 1 / pow(sd.hood, 2); sd.hood ~ dnorm(0, 10)|(0, )
for (p in 1:Nward) { # electoral wards
  gamma2[p] ~ dnorm(0, tau.ward)
}
tau.ward <- 1 / pow(sd.ward, 2); sd.ward ~ dnorm(0, 10)|(0, )
for (p in 1:Nzone) { # police zones
  gamma2[p] ~ dnorm(0, tau.zone)
}
tau.zone <- 1 / pow(sd.zone, 2); sd.zone ~ dnorm(0, 10)|(0, )
for (i in 1:Narea_16) { # lower-level (centered parameterization)
  u[i] ~ dnorm(alpha, tau.u)
  uns[i] <- u[i] - alpha
}
alpha ~ dflat()
(t in 1:T) { # temporal effects
  time[t] <- t
  zeta[t] ~ dnorm(mu.zeta[t], tau.t)
  mu.zeta[t] <- bknot * (time[t] - meantime)
  zeta_model[t] <- zeta[t] - meanzeta
}
bknot ~ dnorm(0, 0.001) # linear trend for temporal effects
meantime <- mean(time[1:T])
meanzeta <- mean(zeta[1:T])
tau.u <- 1 / pow(sd.u, 2); tau.t <- 1 / pow(sd.t, 2); tau.r <- 1 / pow(sd.r, 2) # precision for random
effects
sd.u ~ dnorm(0, 10)|(0, ); sd.t ~ dnorm(0, 10)|(0, ); sd.r ~ dnorm(0, 10)|(0, ) # sd for random effects
w ~ dnorm(0, 0.001) # electoral ward coefficient
for (n in 1:2) {
  b[n] ~ dnorm(0, 0.001) # lower-level coefficient
}
for (n in 1:4) {
  kappa[n] ~ dnorm(0, 0.001) # lower-level coefficient }}

```