

**Spatial Patterns of Neighbourhood Crime in  
Canadian Cities: The Influence of  
Neighbourhood and City Contexts**

by

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## **Author's Declaration**

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

## **Abstract**

The main goal of this study is to investigate the spatial patterns of police-reported crime rates across select Canadian urban neighbourhoods and to explore their relationships with both neighbourhood- and city-level characteristics, as well as neighbourhood spatial dependence. Analyses were based on aggregated data from the 2001 Incident-Based Uniform Crime Reporting Survey (UCR2) and the Census of Population for six Canadian cities: Edmonton, Halifax, Montreal, Saskatoon, Thunder Bay and Toronto. Exploratory spatial data analysis (ESDA) was used to examine the spatial distribution of crime as well as to test for spatial dependence in the crime data. By using multilevel modelling and spatial regression techniques, neighbourhood violent and property crime rates were modeled respectively as a function of both city- and neighbourhood-level contextual variables while controlling for spatial dependence. The results show that crime is not distributed randomly, but tends to be concentrated in particular neighbourhoods, notably around the city centers of these cities. Neighbourhood variance in crime rates is not only dependent on local neighbourhood characteristics, but also on the characteristics of surrounding neighbourhoods, as well as the broader city environment where neighbourhoods are embedded. These findings suggest that strategies aimed at preventing or reducing crime should be developed in light of specific local neighbourhood contexts, while taking into account social forces external to the immediate neighbourhood in the wider social environment.

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# **Chapter 1 Introduction**

## **1.1. Introduction**

There is a rich tradition of research on the spatial distribution of crime. Dating back to the pioneering work of Guerry and Quetelet in the 19th century, research has long demonstrated that crime is not distributed randomly across space. Knowledge about the place where crime occurs can yield powerful insights into the underlying dynamics of crime (Messner et al., 1999). The last two decades have seen growing interest in ecological studies of crime derived from the Chicago School's urban studies (Park and Burgess, 1925; Shaw and McKay, 1942), which seek to identify the characteristics of ecological areas (e.g., country, city, and neighbourhood) that account for crime variation among geographic units (Pratt and Cullen, 2005). In particular, neighbourhood crime has been the most vibrant arena for ecological crime research and numerous studies have documented that several neighbourhood characteristics, such as poverty, ethnic heterogeneity, residential mobility and family disruption are associated with neighbourhood variance in crime rates (e.g., Shaw and McKay, 1942; Wilson, 1987; Sampson and Groves, 1989; Elliott et al., 1996; Sampson et al., 1997).

The cumulative weight of this evidence is impressive; however, it offers a limited perspective on how crime and social context is related. First, with few exceptions (e.g., Kitchen, 2006; Van Wilsem, 2006; Weijters et al., 2009) most studies consider neighbourhoods in one urban area at a time, implicitly assuming that variation across cities is trivial (e.g., Savoie, 2008a; Charron, 2008, 2009). Second, these studies have focused exclusively on the internal properties of neighbourhoods while ignoring the wider social environment within which neighbourhoods are

embedded (e.g., city). As a result, questions remain regarding whether such neighbourhood-level models can be generalized across cities and whether social contexts beyond neighbourhoods can have an impact on neighbourhood crime rates. Moreover, previous studies modelling the effects of neighbourhood characteristics on crime largely relied on the classic statistical models that are based on the assumption of independence between observations. The results of such analyses tend to be biased since both crime data and other socioeconomic data are seldom spatially independent (Baller et al., 2001).

Using data from different Canadian cities, the present study addresses each of these limitations by showing how the relationship between crime and social contexts can be better understood by including multiple social contexts instead of solely the neighbourhood and by taking spatial dependency into account. Specifically, this study aims to investigate the spatial patterns of police-reported crime rates across select Canadian urban neighbourhoods and to explore their relationships with both neighbourhood- and city-level characteristics, as well as spatial dependence among neighbourhoods. Analyses are based on aggregated data from the 2001 Incident-Based Uniform Crime Reporting Survey (UCR2) and the Census of Population for six Canadian cities: Edmonton, Halifax, Montreal, Saskatoon, Thunder Bay and Toronto. Exploratory spatial data analysis (ESDA) is used to examine the spatial distribution of crime as well as to test for spatial dependence in the crime data. By using multilevel modelling and spatial regression techniques, neighbourhood violent and property crime rates are modeled respectively as a function of both city- and neighbourhood-level contextual variables with adjustments for spatial dependence.

## **1.2. Structure of the Thesis**

This thesis contains seven chapters with this being the first.

**Chapter 2** – Literature Review: discusses the theoretical background on the relationship between crime and social contexts. Following this, an overview of previous multilevel research and studies of spatial dependence with reference to crime is present.

**Chapter 3** – Research Design: provides the main goal of this study and specific research questions. Study area and data sources are also described.

**Chapter 4** – Methodology: establishes the analytical framework for this study and describes the research methodologies used, with emphasis on exploratory spatial data analysis (ESDA) and multilevel modelling techniques.

**Chapter 5** – Exploratory Spatial Data Analysis: results generated from the ESDA are presented.

**Chapter 6** – Multilevel Analysis: results of the multilevel models are presented.

**Chapter 7** – Discussion and Conclusion: presents a discussion on the findings and the implications of this study. The recognised limitations of this study are also described with potential further work suggested. The chapter concludes with a reflective outline of the potential contribution of this study.

## **Chapter 2 Literature Review**

### **2.1. Theoretical Background for Crime and Social Contexts**

An overview of the literature reveals that crime research has developed along two fundamental lines. Micro-individual analyses focus on differences in social behavior across types of individuals that differentiate criminals from noncriminals (Gottfredson and Hirschi, 1990; Moffitt, 1993; Sampson and Laub, 1993; Tittle, 1995; Colvin, 2000), whereas macro-ecological analyses emphasize the role of social contexts in explaining crime variation among spatial units (e.g., neighbourhood, city, country) (Park and Burgess, 1925; Shaw and McKay, 1942). Spatial differences in crime have been well documented in criminological research across various levels of spatial units (Van Wilsem, 2003), such as street blocks (Smith et al., 2000; Taylor, 1997), neighbourhoods (Morenoff et al., 2001; Zhang and Peterson, 2007), cities and metropolitan areas (Blau and Blau, 1982; Land et al., 1990; Sampson, 1986a), and countries (Bennett, 1991; Van Wilsem, 2003).

Research seeking to explain the geographic variance of crime has long been a vibrant area of interest for criminologists, sociologists and geographers. Dating back to the early nineteenth century, cartographers such as Guerry (1833) and Quetelet (1847) for the first time empirically examined differences in crime rates between geographical areas (Bruinsma, 2007). Contemporary theory on the spatial distribution of crime, however, has more specific roots in the ecological theories growing out of the Chicago school's urban studies at the beginning of the twentieth century (Andresen, 2006). The distinguished works of Park and Burgess (1925), Wirth (1938), and Shaw and McKay (1942) established a set of theories that underpinned the ecology of crime in the city and influenced all subsequent geographical research in criminology

(Bruinsma, 2007; Herbert, 2001). Compared to criminological theories that traditionally focus on the individual characteristics of offenders or victims, ecological theories of crime highlight the role of social contexts, such as the social, economic and demographic attributes of places, in influencing the level and type of crime experienced in an area or community (Kitchen, 2006).

Several theories have emerged and developed to deal with this issue, each focusing on different social mechanisms, such as economic deprivation, social control and people's lifestyles (Van Wilsem, 2003). The following sections introduce key ideas from three dominant ecological theories of crime: strain theory (Merton, 1938), social disorganization theory (Shaw and McKay, 1942) and routine activity theory (Cohen and Felson, 1979).

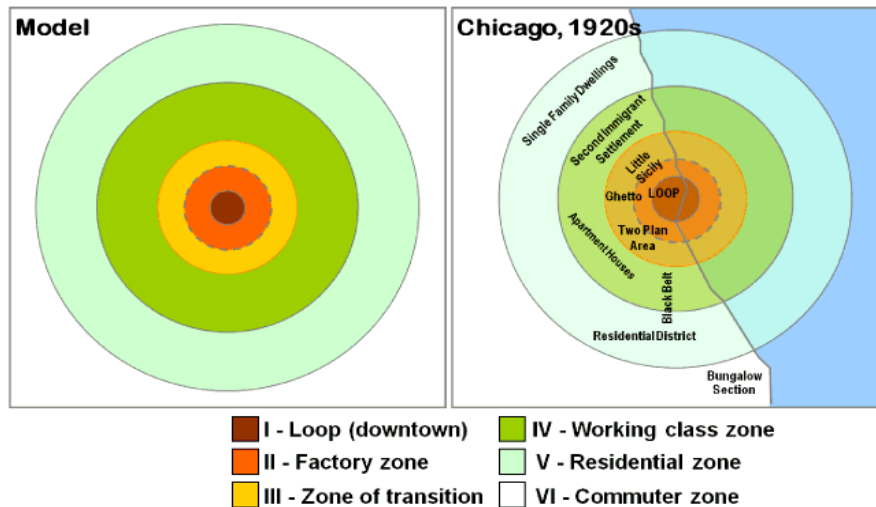
### **2.1.1. Strain/Anomie Theory**

The Merton's (1938) "strain" theory is one of the main ecological theories on the explanation of geographic differences in crime. The core notion of this theory is how culture and social structure may contribute to high crime rates (Messner, 1988). In Merton's view, American culture places material success at the pinnacle of social desirability, which, however, is not matched by a concurrent normative emphasis on the legitimate means to achieve the desired goals (Pratt and Cullen, 2001). Even worse, the structural barriers of society (e.g., structural barriers to women, blacks, poor) tend to limit individuals' access to the legitimate means for attaining economic success, which, in turn, produces structural strain or pressure on the cultural norms that guide how to reach the culturally prescribed goal (e.g., pecuniary success) legally (Merton, 1968). The weakening of cultural norms or so-called "anomie" (Durkheim, 1951) may increase deviant behavior and crime within social aggregates (Pratt and Cullen, 2001). Following the initial work of Merton, several researchers extended this theory to explore the impact of economic deprivation and economic inequality on delinquency and crime, such as Blau and Blau

(1982), Messner (1982, 1983a, 1983b) and Bailey (1984). They contributed to stress either the role of absolute deprivation (e.g., family income below the poverty level) or relative deprivation (e.g., income inequality) in the explanation of crime variance (Bailey, 1984; Blau and Blau, 1982; Messner, 1982, 1983a, 1983b). Although strain/anomie theory is an offender-oriented perspective that identifies social mechanisms that induce criminality, it can be used as a contextual explanation for crime distribution (Van Wilsem, 2003). To date, the empirical tests of strain theory have been done at the macro-level across a variety of spatial units, such as neighbourhoods (Messner and Tardiff, 1986), metropolitans (Blau and Blau, 1982; Messner, 1982), states (Ehrlich, 1973), and countries (Messner, 1983b).

### **2.1.2. Social Disorganization Theory**

Social disorganization theory finds its root in the classical Chicago School studies of urbanization. Using Chicago as a case study, Park and Burgess (1925), elaborated a theory of urban ecology and developed the “concentric zone model”, which suggested that cities tended to expand from the center and form five concentric zones (Figure 2.1) with areas of social and physical deterioration concentrated near the city centre and more prosperous areas located near the city's fringe (suburbs). In particular, they highlighted the “zones in transition” located around the city centre as problem areas since they frequently experienced social change and conflict due to the continuous and rapidly-growing invasion of central business district (downtown), which may result in a breakdown of social control structure. Consequently, communities in the transition zone were more likely to suffer from a lack of normative structure and higher rates of social problems (Roh and Choo, 2008).



**Figure 2.1** - Burgess's concentric zone model

Source: Jean-Paul Rodrigue. 1988. Hofstra University. The Burgess Urban Land Use Model. Hempstead, NY.  
<http://people.hofstra.edu/geotrans/eng/ch6en/conc6en/burgess.html>

As supporters of the ecology approach, Shaw and McKay (1942) applied the concentric zone model to the study of juvenile delinquency in Chicago and provided perhaps the earliest work on social disorganization theory. They observed that crime rates tended to be higher in the communities closest to the city centre (transition zone), which were characterized by low socio-economic status, high numbers of ethnic/racial minorities and high residential mobility (Wilcox et al., 2003). Evolved from their initial works, social disorganization theory suggests that socioeconomic stress, such as poverty, residential instability, and ethnic heterogeneity either tends to disrupt social networks or prevent such networks from forming. These networks are responsible for most social control and community cohesion in neighborhoods, therefore their absence possibly leads to higher levels of delinquency and crime (Ackerman, 1998; Bursik, 1988). Essentially, this theoretical framework relates several structural factors that are assumed to be the antecedents of “social disorganization” (e.g., urbanism, poverty, residential instability, and ethnic heterogeneity) to crime.



The Shaw and McKay's perspective on social disorganization has been extended by a number of researchers, who commonly viewed social disorganization through a social control model (Sampson, 1986b; Bursik, 1988; Sampson and Groves, 1989). For example, Sampson (1986b) argued that family disruption does affect neighborhood delinquency rates since it weakens informal social controls on the behavior of children. Sampson and Groves (1989) demonstrated that the effects of structural characteristics identified by Shaw and McKay (e.g., poverty, residential instability, and ethnic heterogeneity) have been mediated by several formal and informal community control factors, such as local friendship network, a community's ability to supervise and control teenage peer groups and participation in formal and voluntary organizations (Sampson and Groves, 1989). In a similar vein, some researchers used either "social ties" (e.g., Elliott et al., 1996; Bellair, 1997, 2000; Markowitz et al., 2001) or "social capital" (e.g., Hirschfield and Bowers, 1997) as a measure of collective social control within a community and found evidence that communities with stronger social ties and those with high stocks of social capital tend to be more effective in exercising informal social control against crime problems. Similarly, Sampson et al., (1997) constructed a concept of "collective efficacy", which refers to "social cohesion among neighbours combined with their willingness to intervene on behalf of the common good" (Sampson et al., 1997). In a study of violent crime in Chicago neighbourhoods, Sampson et al. (1997) found collective efficacy largely reduced the effect of concentrated disadvantage and residential instability on violence (Kubrin and Weitzer, 2003b).

However, compared to the original version of social disorganization theory, such extended ones (social ties, social capital, and collective efficacy) have not been fully tested in empirical works due to the difficulty of translating them into measures that directly tap hypothesized constructs (Sampson and Raudenbush, 1999, Kubrin and Weitzer, 2003b). In addition, social

disorganization theory has been criticized for its propensity to overemphasize on the characteristics of place while overlooking those of the individuals (e.g., individual psychology, distinctive biology, personal choice on criminal activity) (Schmalleger and Volk, 2001).

### **2.1.3. Routine Activity Theory**

Another broad theoretical tradition, which addresses some of the criticisms of social disorganization theory, is routine activity theory and related opportunity theory (Cohen and Felson, 1979). Unlike traditional theories of crime, which largely focus on the role of offenders or potential offenders, routine activity theory assumes the existence of motivated offenders while emphasizing the importance of opportunity in understanding the occurrence of crime (Cohen and Felson, 1979; Felson and Cohen, 1980). This theory argues that for a criminal event to occur there should be a convergence of three necessary components in space and time: the presence of a likely offender, the presence of a suitable target and the absence of a capable guardian (Cohen and Felson 1979). Therefore, rates of crime or victimization tend to be highest in those areas where motivated criminals are most likely to encounter attractive and unguarded targets (Pratt and Cullen, 2005). In reality, the likelihood of this convergence occurs is largely shaped by the social organization of daily life or the "routine activity" in which people are engaged (Pratt and Cullen, 2005). Accordingly, many empirical tests of this theory seek to identify the characteristics of people that influence their routine activity patterns and thus their risk of involvement in crime as either victims or perpetrators. Foremost among these are some demographic characteristics of population, such as gender, age, race, and marital status (Cohen and Cantor, 1980; Cohen et al., 1981; Laub, 1997). For example, many studies demonstrated the relative concentration of population in the teenage and young adult ages (e.g., ages 15-29) will

provide greater supply of both offenders and victims as their lifestyles place them in situations conducive to crime (Hirschi and Gottfredson, 1983; Land et al., 1990).

Also, a central perspective of the routine activity model is the distribution of crime or victimization across space can be explained in terms of opportunity. Several variables that indirectly measure the availability of targets and offenders include population size, population density, unemployment rate, and the level of manufacturing employment (e.g., Land et al., 1995). Furthermore, it has been widely acknowledged that land use can influence opportunity structures for crime. In particular, several studies show that a large proportion of mixed or nonresidential landuse, especially the land used for businesses, attracts more strangers and creates an anonymous environment, thus potentially impeding the ability of residents to maintain effective social control and accordingly provide more opportunities for crime (Kurtz et al., 1998; Taylor et al., 1995; Wilcox et al., 2004; Stucky and Ottensmann, 2009). Some studies have addressed how particular physical features and the related use of land, such as bars (Roncek and Maier, 1991), schools (Roncek and Lobosco, 1983), public housing sites and major thoroughfares (Suresh and Vito, 2007) can affect crime rates in their immediate environment depending on the type of people attracted, the way the space is managed, and possible guardian present in these facilities (Sherman and Weisburd, 1995).

In addition, it has been argued that physical processes related to the use of the land, such as physical deterioration, disorder and incivilities may also mediate the impact of landuse on crime in neighbourhoods (Kurtz et al., 1998; McCord et al., 2007; Taylor et al., 1995; Wilcox et al., 2003; Stucky and Ottensmann, 2009). This argument is in line with broken window theory (Wilson and Kelling, 1982), which suggests the degradation of physical environment (e.g., the presence of vacant buildings, empty lots, garbage, graffiti, and abandoned cars) may engender a

sense of not caring and ambivalence, thus leading to further deterioration of social cohesion within the community that would otherwise favor social control of crime (Brown et al., 2004; Charron, 2009).

To date, routine activity theory has been used to explain the variation in crime at both individual and aggregate levels of analysis (Van Wilsem, 2003), such as differences in crime rates across geographical units, changes in crime rates over time and individual's risk of victimization (e.g., Kennedy and Forde, 1990; Miethe and McDowall, 1993; Sampson and Wooldredge, 1987).

## **2.2. Multilevel Studies of Crime**

Much crime research frequently involves using hierarchically structured data (i.e., data in which the units of analysis are grouped or nested). A common example of hierarchical data is those data collected from individuals nested within groups or geographic units, such as juvenile offenders grouped by their schools, crime offenders or victims grouped by their neighborhood of residence. Moreover, in longitudinal research that analyzes individuals over time, repeated measurements for any particular individual are nested in a group (e.g., offences grouped by the offenders who committed them). Despite the prevalence of hierarchical data, many crime studies in the past failed to address them adequately due to the limitation of traditional regression models that represent the hierarchical structure merely at a single level. However, the hierarchical structure of data implies potential dependence of observations within groups (e.g., individuals within a group are similar to the extent that they share common experiences due to closeness in space or time), which violates the assumption of traditional statistic methods (e.g., OLS) that observations are independent (Kreft and De Leeuw, 1998; Diez-Roux, 2000). This may lead to significant statistical costs as estimated standard errors that are biased downward and Type I error rates that

are much larger than the nominal alpha level (Hox and Kreft, 1994). As a consequence, Type I errors are more frequent and there is an increased tendency to find a significant effect of predictors where none exist (Duncan et al., 1998). Therefore, applying traditional regression models to hierarchical data may produce biased results and misleading conclusions.

Fortunately, since the mid-1980s, multilevel regression models (also known as hierarchical linear models) (Raudenbush and Bryk, 2002) have been developed to allow researchers to control for the potential dependence of observations involved in crime data. Furthermore, multilevel models also permit a partitioning of the variance in an outcome into between- and within-group components to allow separate estimation of the effects at each level (Elliott et al. 1996). In this way, many criminological research questions can be answered with more conclusive empirical findings, since the hypothesis on relationships between crime and relevant factors at one level can be tested more strictly by controlling for the confounding effects of factors measured at other levels. In addition, multilevel models allow estimation of cross-level interaction, that is, the interactions between variables defined at different levels of the hierarchy (Diez-Roux, 2000). This is a major improvement over traditional single-level analysis of crime, since it offers enhanced opportunity for crime researchers to determine whether the relationships between individual-level factors and crime are conditioned by, or vary with, the broader social contexts (Rountree et al., 1994).

Over the past few years, multilevel models have been used in various crime research fields, such as victimization (e.g., Sampson and Wooldredge, 1987; Rountree et al., 1994; Velez, 2001; Van Wilsem, 2003; Wittebrood and Nieuwbeerta, 2000), adolescent development (e.g., Elliott et al. 1996), youth delinquency (e.g., Anderson, 2002; Oberwittler, 2002, 2004; Weijters et al. ,2009), violence (e.g., Sampson et al., 1997) and fear of crime (e.g., Fitzgerald, 2008; Wyant, 2008).

Most of this body of research focused on examining how neighbourhood characteristics interact with individual-level attributes to influence a given individual-level outcome. For example, Rountree et al. (1994) integrated individual routine activities and lifestyle variables and neighbourhood-level social disorganization variables into hierarchical logistic regression models of violent and burglary victimization, using the sample of residents in 300 Seattle neighbourhoods. In addition to documenting the direct effects of three neighbourhood social disorganization variables (measures of disorder, ethnic heterogeneity and neighbourhood density) on violent and burglary victimization risk, they found evidence that neighbourhood contexts also conditioned or contextualized individual-level relationships, as the relationships of individual routine activities and lifestyle characteristics to violent and burglary victimization differed significantly across Seattle neighbourhoods.

A few studies attempted to disentangle contextual effects (e.g., neighbourhood characteristics) from compositional effects (individual-level mechanisms) in shaping aggregated crime outcomes (e.g., neighbourhood crime rates) (e.g., Weijters et al., 2009; Van Wilsem, 2003; Fitzgerald, 2008). For example, Fitzgerald (2008) employed multilevel logistic regression models to examine whether the chances of experiencing fear of crime varied across Canadian urban neighbourhoods, and whether this variation can be accounted for by the socioeconomic and demographic features of neighbourhoods, over and above the individual characteristics of residents who live there. The findings indicated that fear of crime varied significantly across Canadian urban neighbourhoods and this neighbourhood variation was not completely explained by neighbourhood characteristics, rather more of it was attributed to individual-level sociodemographic characteristics as well as individual perceptions of neighbourhood crime and disorder (Fitzgerald et al., 2008).

To date, multilevel analyses of crime have been largely limited to focusing simultaneously on individual and neighbourhood contexts, while seldom examining social conditions in other contexts that may also have an impact on crime. It has been argued that other ecological contexts beyond neighbourhoods should be identified when examining contextual effects (Oberwittler, 2002, 2004; Van Wilsem, 2003; Kubrin and Weitzer, 2004b). For example, Oberwittler (2002) claimed that the school constitutes an ecological context of its own right which simply cannot be subsumed to the community (neighbourhood) context. A limited number of multilevel studies in criminological research have used the school as a context for delinquency (Anderson, 2002; Felson et al., 1994). In addition, very few researchers have addressed the role of social contexts larger than neighbourhoods (e.g., city, state) in explaining individual-level victimization (Van Wilsem, 2003) and youth delinquency (Weijters et al., 2009). Nevertheless, until today, little is known about whether city features have independent effects on neighbourhood-level crime rates after adjusting for individual and neighbourhood characteristics.

### **2.3. Modeling Spatial Dependency of Crime**

It has been well recognized that spatial data such as crime and census data are intrinsically affected by the properties of the location in which they reside (Anselin, 1994; Baller et al. 2001; Charron, 2009). If adjacent observations are affected by the same location properties, the observations may not be independent of one another (Charron, 2009). The basis for this perspective stems from the Tobler's First Law of Geography which states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). These phenomena are formally indicated by the concept of spatial dependence or spatial autocorrelation, which can be described as the degree to which characteristics at proximal locations appear to be correlated, either positively or negatively (Anselin, 1988).

Spatial autocorrelation is frequently encountered in crime data, which can be simply reflected in the fact that crime is not evenly distributed across space but tends to be concentrated in some places or areas. The importance of spatial dependence has been discussed in the literature on a number of grounds (e.g., Baller et al., 2001; Messner et al., 1999; Morenoff et al., 2001). On the one hand, since spatial dependence conflicts with the usual assumption of independent observations in traditional statistical methods, it is important to include an adjustment for spatial autocorrelation in regression analysis, otherwise it may produce false indications of significance, biased parameter estimates, and misleading suggestions of fit (Messner et al., 1999). On the other hand, spatial dependence can suggest interesting spatial processes underlying the distribution of crime. First, spatial dependence is implicated by the fact that many interpersonal crimes (e.g., assault and homicide) are based on social networks and other media of communication that cross neighbourhood boundaries, and thus may be subject to diffusion processes – acts of violence that occur in one neighbourhood is likely to increase the probability of subsequent violence in adjacent neighbourhoods (Cohen and Tita, 1999; Messner et al., 1999; Rosenfeld et al., 1999; Smith et al., 2000; Morenoff et al., 2001). For example, homicides that occur in one neighborhood may instigate retaliatory killings in a nearby neighborhood (Kubrin and Weitzer, 2003a). Second, crime-related social processes, either risk or protective factors, may spill over neighborhood boundaries to exert external influences beyond the local neighbourhood (Morenoff, 2003). For example, social networks and voluntary associations in a neighbourhood not only help residents to exert social control of crime in those areas but also produce a protective effect against crime in adjacent neighbourhoods.

Although there is strong justification for taking spatial dependence into account when analyzing crime data, a limited number of researchers have done so (e.g., Messner et al., 1999; Baller et al.,



2001; Morenoff et al., 2001; Kubrin and Weitzer, 2003a, Charron, 2008, 2009). Most of these studies have adopted statistics tests (e.g., Moran's I statistic) and spatial regression models (e.g., spatial lag model) to formally identify and explicitly model spatial dependence in the data under investigation. For example, Baller et al. (2001) examined the impact of structural covariates on county homicide rates in the United States from 1960 to 1990 with rigorous controls for spatial processes. In doing so, they firstly carried out the Moran's I statistic to test for spatial dependence in homicide rates. After significant spatial autocorrelation was detected, they employed spatial regression models to formally model this spatial dependence. Similar works have been done by other researchers, such as Charron (2008, 2009), Messner et al. (1999) and Morenoff et al., (2001). According to the review by Kubrin and Weitzer (2003b), to date, every study that assesses the effects of neighbourhood characteristics on crime rates with adjustments for spatial autocorrelation has found significant spatial dependence in the models (Kubrin and Weitzer, 2003b).

In summary, rich insights have been derived from various ecological theories of crime (strain/anomie theory, social disorganization theory, routine activity theory), and substantial empirical research has been done to examine the relationship between social contexts and crime. However, previous studies have largely limited their analysis to a single level with an exclusive focus on the characteristics of local neighbourhoods, while ignoring the potential impact of social contexts overarching neighbourhoods (city) or external to them (other neighbourhoods). Therefore, they provide a limited perspective on how crime and social contexts are related.

# Chapter 3 Research Design

## 3.1. Aim and Objectives of the Research

The main goal of this study is to investigate the spatial patterns of police-reported crime rates across select Canadian urban neighbourhoods and to explore their relationships with both neighbourhood- and city-level characteristics, as well as spatial dependence among neighbourhoods. In particular, key questions the study attempts to address include: (1) how are police-reported criminal incidents distributed across neighbourhoods within the Canadian cities? (2) How can we quantify the relationship between crime rates and their associated neighbourhood factors, such as its socioeconomic, demographic, and dwelling characteristics? (3) Is the crime rate in a neighbourhood influenced by nearby neighbourhoods? (4) Do wider social contexts, such as at the city level, have an impact on neighbourhood crime rates?

In light of these research questions, the objectives of the study can be divided into three parts:

- (1) To examine the spatial distribution of violent and property crime rates across neighbourhoods in each of the six cities respectively (Edmonton, Halifax, Montreal, Saskatoon, Thunder Bay and Toronto);
- (2) To test for spatial dependence in neighbourhood violent and property crime rates for each of the six cities respectively (Edmonton, Halifax, Montreal, Saskatoon, Thunder Bay and Toronto);
- (3) To assess the effects of both neighbourhood- and city-level characteristics on neighbourhood violent and property crime rates with adjustments for neighbourhood spatial dependence.

### **3.2. Study Area**

Similar to other developed countries, a vast majority of Canadians live in urban areas. In particular, about two-thirds of the Canadian population reside in metropolitan areas, defined by Statistics Canada as census metropolitan areas (CMAs), in which the urban core population is greater than 100,000 (England and Mercer, 2006). In total, 27 such areas have been identified by Statistics Canada and they host most of the country's economic, sociocultural and political strength (England and Mercer, 2006). However, it has been shown that on average, the overall levels of crime are higher in urban areas than rural areas, and neighbourhoods within large urban centres are at greater risk in terms of crime (Sherman, 1992; Weisburd and Green, 1994; Bruinsma, 2007). Due to the limitation of time and data availability, we restricted our analyses to neighbourhoods within six Canadian cities: Edmonton, Halifax, Montreal, Saskatoon, Thunder Bay and Toronto. They are the urban cores in their respective CMAs of the same names. We chose the six cities foremost because crime data aggregated to small geographical units (e.g., census tract) for these cities were available. Secondly, the geographical distributions of these cities offer a great opportunity for a comparative study of the spatial patterns of crime and social mechanisms among different urban settings. There is no such thing as a typical city, while the six cities (Edmonton, Halifax, Montreal, Saskatoon, Thunder Bay and Toronto) are dispersed in the five provinces (Alberta, Nova Scotia, Quebec, Saskatchewan and Ontario) that represent Western, Prairie, Eastern and Atlantic Canada.

Table 3.1 presents some characteristics of the six Canadian cities with respect to their population size, age structure, household and family formation, ethnocultural composition and income level. It shows that the six cities share some characteristics that are typical of urban communities in

Canada, such as aging population and declining household size, but they vary dramatically in population size, ethno-culture composition and economic situation.

**Table 3.1** – Selected characteristics of six Canadian cities and Canada as a whole

	Canada	Edmonton	Halifax	Montreal	Saskatoon	Thunder Bay	Toronto
Population	30,007,094	666,104	359,111	1,039,534	196,811	109,016	2,481,494
Percentage of lone parent families (%)	15.7	18.2	16.5	21.8	19.3	19.2	20.3
Percentage of one person household (%)	25.8	30.2	27.7	39.6	30.8	31.5	30.2
Percentage of immigrants (%)	18.2	24.9	7.6	47.2	8.5	10.7	49.9
Percentage of Aboriginal (%)	4.5	5.3	1.4	0.5	9.9	8.2	0.5
Median age	37.6	35.3	36.6	37.9	34.3	39.9	36.9
Unemployment rate	7.4	4.9	6.3	9.2	5.5	7.2	7.6
Median household income (\$)	46,752	46,698	46,946	31,771	41,991	46,072	49,345
Prevalence of low income families after tax in 2000 (%)	16.2	15.4	11.9	26.5	14.7	11.1	19.4

Data Source: 2001 Canadian Census of Population, Statistics Canada

The variance in socioeconomic, demographic characteristics among the six cities may partially account for their differences in police-reported crime rates. Figure 3.1 illustrates the general trends in crime rates as reported by police services in the above six cities and Canada as a whole during the last decade (1998 to 2009). In general, these six cities display two different patterns with respect to the changes in crime rates over time. One pattern is shown in Montreal and Toronto, both of which followed the downward trend in crime rate observed nationwide during the same period, remaining lower than the rate for Canada overall. By contrast, the other four cities, Edmonton, Halifax, Saskatoon and Thunder Bay, show more complex patterns of changes in crime rates, which fell first and then increased and dropped again during 1998 and 2009 (except for Thunder Bay with a slight increase in 2009), while remaining higher than the national

level. Among them, Saskatoon had the highest crime rates during all these years, although it witnessed an unprecedented decline in crime rate since 2003. By contrast, the crime rates reported by the Toronto Police Service have been below those of all other five cities during 1998 and 2009. It seems that unlike the popular trend observed in other countries (e.g., the United States), the largest cities in Canada (e.g., Montreal, Toronto) did not experience higher police-reported crime rates than smaller cities (e.g., Saskatoon). However, given the substantial variance among six cities in the population used to calculate crime rates (see Table 3.1), the crime problem in cities with large population size might be underemphasized.

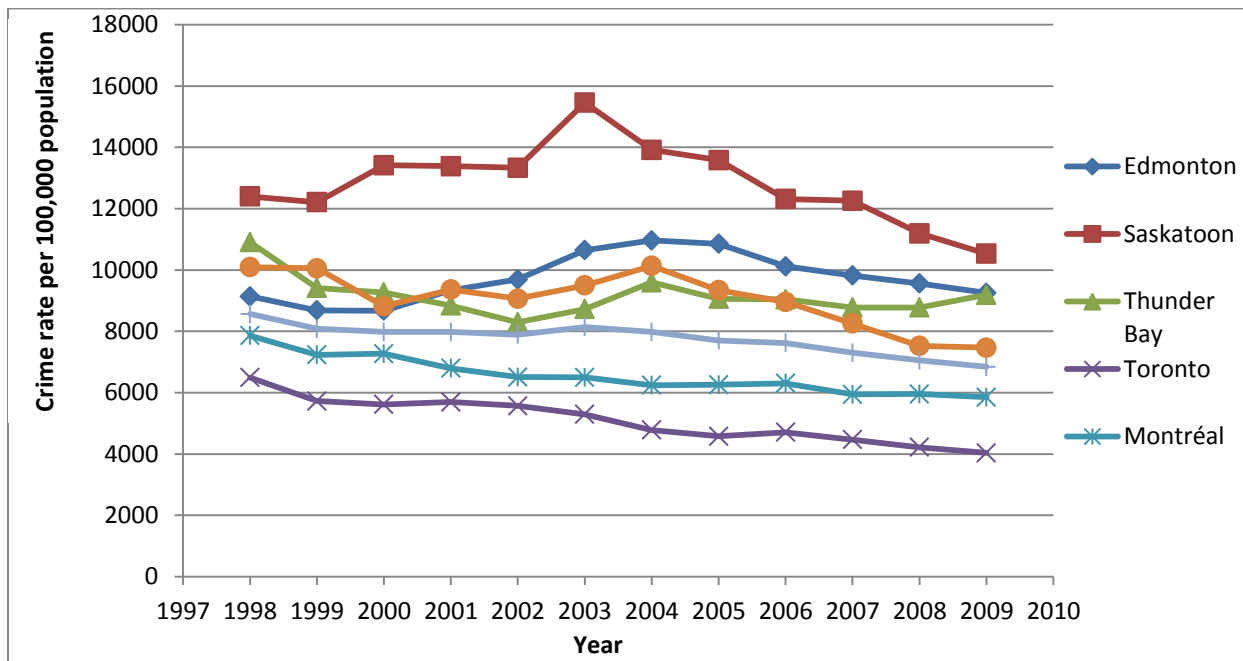


Figure 3.1 - Crime rates <sup>1</sup> in selected cities, Canada, 1998 to 2009

1. Rates based on count of total Criminal Code incidents excluding traffic offences.  
 Data Source: Statistics Canada, Canadian Centre for Justice Statistics, Uniform Crime Reporting Survey, 1998 to 2009.

### **3.3. Data and Measure**

#### **3.3.1. Crime Data**

This study was based on police-reported data derived from the Incident-based Uniform Crime Reporting (UCR2) Survey for six Canadian cities: Halifax, Edmonton, Montreal, Saskatoon, Thunder Bay, and Toronto. According to the data availability, except for Toronto, for which the crime data were derived from the 2006 UCR2 Survey, the crime data for other five cities were from the 2001 UCR2 Survey. It should be noted that since the crime data were drawn from data reported by the police, they provide a particular perspective on the nature and extent of crime. In other words, there may be some criminal incidents that did not come to the knowledge of the police (Wittebrood and Junger, 2002). Many factors can influence police-reported crime data, such as underreporting, changes in legislation, and policies or enforcement practices, which may constrain their effective use (Charron, 2009). Despite these limitations, however, police-reported crime data have been considered as the most comprehensive and reliable data source for providing critical information of time, place and type of crime (Nelson and Bromley, 2001).

The Incident-based Uniform Crime Reporting (UCR2) Survey data contain detailed information on individual criminal incidents reported to the police, such as characteristics of incidents, accused people and victims (CCJS, 2008). Analyses in this study focused on the major offence categories: violent offences (offences against person) and property offences (offences against property). Violent offences include homicide, attempted murder, and various forms of sexual and non-sexual assault, robbery and abduction. Traffic incidents that result in death or bodily harm are also included under the Criminal Code (CCJS, 2008). Property offences include arson, break and enter, theft over \$5,000, theft \$5,000 and under, motor vehicle theft, have stolen goods, fraud

and mischief (CCJS, 2008). Under this classification, a higher priority is given to violent offences than to property offences since only the most serious offence (related to the maximum sentence that can be imposed under the Criminal Code) is recoded per criminal incident. Accordingly, less serious offences may be under-represented when only the most serious offence is considered. Moreover, the UCR2 Survey includes most Criminal Code offences and all offences under the Controlled Drug and Substances Act, but it excludes offences under other federal and provincial statutes and municipal by-laws, or Criminal Code offences for which there is either no expected pattern of spatial distribution or a lack of information about the actual location of the offence (Charron, 2009). Excluded violations include impaired driving, harassing phone calls and offences against the administration of justice (CCJS, 2008).

Due to the highly confidential nature of crime, only aggregated data, the totals of criminal incidents by violent and property offence aggregated to census geographic units were available. More specifically, crime data for Halifax, Edmonton, Montreal, Thunder Bay and Toronto were aggregated to the census tract (CT) level, while those for Saskatoon were aggregated to the dissemination area (DA) level. According to Statistics Canada, a census tract is “a small, relatively stable geographic area that usually has a population of 2,500 to 8,000”, while a dissemination area is “a small area composed of one or more neighboring blocks, with a population of 400 to 700 persons” (Statistics Canada, 2001a). Therefore, in this study we used the lowest level of areal aggregation obtainable (CTs/DAs) rather than the individual case as the smallest unit of analysis. In other words, neighbourhoods in this study were defined by the census geographic units (e.g., neighbourhoods corresponding to census tracts or dissemination areas).

Using CT/DA as the unit of analysis offers several advantages for the purpose of this study. First, both CTs and DAs are predefined administrative geographic units, making it easier to add layers of additional information (socioeconomic, demographic, landuse factors etc.) for a relatively full-scale investigation on the social contexts and crime (Savoie et al., 2006). Second, CTs have been recommended by previous research as the most appropriate unit in the study of neighbourhood crime (Krivo and Peterson, 1996; Zhang and Peterson, 2007; Ouimet, 2000). Some researchers pointed out that CT is small enough to maintain sufficient variation in population characteristics so that can improve the statistical power of the findings (Ouimet, 2000). Others argued that CT is large enough to capture an adequate number of population for constructing reliable crime rates (Krivo and Peterson, 1996).

Despite the desirable features of CTs/DAs, there are some limitations associated with these units need to be noted. One of the most significant problems is the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984). The aggregated characteristics of CTs/DAs may be as much a function of their size, shape and orientation, which may lead to uncertain results of analysis and unreliable inference. Second, both CTs and DAs are administrative units which are arbitrary in nature, and therefore they may not match the ecological notion of neighbourhood. For example, they may split residents who are identified with each other as “neighbors” in reality into different census geographic units (Kubrin and Weitzer, 2003b). Finally, analyses based on aggregated data are susceptible to the so-called “ecological fallacy” problem, which can occur when an inference is made about the characteristics of individuals based only upon aggregated statistics collected for the group to which the individuals belong (Robinson, 1950). Therefore, the relationship between crime rates and neighbourhood characteristics measured at the CT or DA level does not necessarily represent the relationship that exists at the individual level.



### **3.3.2. Census Data**

Data on neighbourhood characteristics were drawn from the Canadian Census of Population conducted by Statistics Canada every five years. It provides not only the population and dwelling counts but also the information about Canada's demographic, social and economic characteristics for different levels of geographic units (e.g., country, province/territory, CMA/CA/UA, CT, and DA etc.). The detailed socioeconomic, demographic and dwelling variables used in this study are derived from the long form of the census, which is collected from a 20% sample of households (Savoie, 2008b). These data exclude the institutional population, including people living in hospitals, nursing homes, prisons and other institutions (Savoie, 2008b). To achieve the highest degree of compatibility between crime and contextual information, this study was drawn on crime data and census data from the same year<sup>1</sup> (2001). A summary of the datasets and specific variables is shown in Table 3.2.

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<sup>1</sup> Although crime data for Toronto were from 2006, neighbourhood independent variables for Toronto were drawn from 2001 Census, in order to keep consist with other cities.

**Table 3.2** – Dependent and independent variables

<b>Dependent Variable</b>	<b>Description</b>	<b>Data Source</b>
Violent/Property crime rate	The number of violent/property incidents per 1,000 combined working and residential population	2001/2006 Incident-based Uniform Crime Reporting (UCR2) Survey from the Canadian Centre for Justice Statistics (CCJS)
<b>Neighbourhood-level Independent Variables</b>	<b>Description</b>	<b>Data Source</b>
Index of Concentration at the Extremes (ICE)	The number of affluent families (economic families whose after-tax income > \$100,000) minus the number of low-income families (economic families spend 20% more than average on food, shelter and clothing), divided by the total number of families in the neighbourhood	2001 Canadian Census of Population from Statistics Canada
Percentage of Aboriginal population	Percentage of neighbourhood residents who reported identifying with at least one Aboriginal group, that is North American Indian, Métis or Inuit (Eskimo), who reported being a Treaty Indian or a Registered Indian as defined by the Indian Act of Canada, or who reported they were members of an Indian Band or First Nation	
Percentage of dwellings built before 1961	Percentage of dwellings built before 1961 in the neighbourhood	
Percentage of dwellings that require major repairs	Percentage of dwellings in need of major repairs in the neighbourhood	
Percentage of lone-parent families	Percentage of lone-parent families among economic families living in private households in the neighbourhood	
Percentage of multifamily household	Percentage of dwellings that are considered multifamily occupied houses in the neighbourhood	
Percentage of owner-occupied household	Percentage of owner-occupied dwellings in the neighbourhood	
Percentage of people who are single	Percentage of neighbourhood residents aged 15 and older who have never been married	
Percentage of young males	Males aged 15 to 24 as a percentage of the total neighbourhood residents	
Percentage of population aged 65 years and over	Percentage of neighbourhood residents who are 65 years and older	
Percentage of recent immigrants	Percentage of neighbourhood residents who immigrated to Canada in the last decade (1991-2001)	
Percentage of residents in low-income households	Percentage of neighbourhood residents in private households that spend 20% more of their disposable income than the average private household on food, shelter and clothing	

Percentage of residents without high school diploma	Percentage of neighbourhood residents aged 20 and older without a high school diploma	
Percentage of visible minorities	Percentage of persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in color account for the neighbourhood population	
Population density	Number of people per square kilometer in the neighbourhood	
Residential stability	Percentage of neighbourhood residents aged 5 years and over who were living at the same address five years earlier	
Unemployment rate	Percentage of neighbourhood residents aged 15 and older unemployed expressed as a percentage of the labour	
<b>City-level Independent Variables</b>	<b>Description</b>	<b>Data Source</b>
Population	Total number of inhabitants in the city	2001 Canadian Census of Population from Statistics Canada
Population per police officer	The population of the area (city) serviced by the police service divided by the number of police officers	2001 Police Administration Survey from the Canadian Centre for Justice Statistics (CCJS)

### 3.3.3. Variables and Measures

#### 3.3.3.1. Dependent Variable: Crime Rate

Standardization is a useful way of representing data for a set of areas where the areas differ in size (raw data would tend to overemphasize large areal units) or where it is necessary to take the underlying population into account (Haining, 2003; Ceccato and Haining, 2005). Population-standardized crime rate is mostly defined as the number of incidents committed in a given area standardized by the population at risk, which normally refers to the residential population of a given area (Zhang and Peterson, 2007). This method offers good results at large or median level (e.g., municipal, provincial and national) but it may lead to some problems for smaller level (e.g.,

census tract, block) since for many incidents, neither criminals nor victims necessarily live in the same area where the crimes are committed (Goldsmith et al., 2000; Osgood, 2000; Roncek, 2004). Especially for those areas containing small residential population and large transient population, such as neighbourhoods in the city centre, the rates based on residential population alone will artificially inflate the crime rates in these areas, as the number of residents is not representative of the coming, going and gathering that occupy one place regularly (Charron, 2009). Therefore, the sum of working and residential population by CT/DA from the UCR2 Survey was used to approximate the total number of people at risk of experiencing crime in an area in this study. For CT/ DA included, the crime rate for violent and property offence type was respectively calculated and expressed as the number of incidents per 1,000 combined working and residential population.

### **3.3.3.2. Neighbourhood-level Independent Variables**

In order to examine the effects of social contexts on neighbourhood crime rates, the study was drawn on the key theoretical concepts from strain/anomie theory (Merton, 1957), social disorganization theory (Shaw and McKay, 1942) and routine activity theory (Cohen and Felson, 1979). Accordingly, we hypothesized that certain characteristics located at the city level as well as at the neighbourhood level can influence neighbourhood crime rates. A wide range of variables have been well established by previous research as predictors of crime. However, we focused on variables that were most frequently used by the literature and available from the current dataset. In total, 17 census variables at the neighbourhood level and 2 city-level variables were selected (Table 3.2). In general, the select neighbourhood characteristics can be classified into four different dimensions: socioeconomic characteristics, demographic characteristics,

ethno-cultural characteristics and dwelling characteristics. The following sections describe these variables and discuss their potential associations with crime.

#### **3.3.3.2.1. Socioeconomic Characteristics**

In support of social disorganization theory and strain/anomie theory, several studies have demonstrated that residents' limited access to socioeconomic resources can be associated with local crime rates (Massey, 1996; Body-Gendrot, 2001; Forrest and Kearns, 2001; Bauder, 2002; Charron, 2009).

In this study, access to socioeconomic resources was measured in part by a number of census variables, each covering a specific aspect of it. For example, low education attainment (the percentage of residents without high school degree) and unemployment rates provided a partial and indirect measure of neighbourhood residents' inability to obtain income from stable paid employment. The percentage of residents living in low-income households was included as a measure of economic deprivation rooted in Merton's strain theory (Merton, 1957). On the other hand, recent studies have shown that affluence is more than just the absence of disadvantage and there is growing interest in sociology to measure the upper tail of income distribution to assess its separate effects (Sampson et al., 2001). Some researchers have argued that concentrated affluence generates a separate set of protective mechanisms in a neighbourhood based on access to social and institutional resources (Brooks-Gunn et al., 1993). Therefore, we included the index of concentration at the extremes (ICE) (Massey, 2001), which measures the degree of concentrated affluence relative to the concentration of poverty in a neighborhood, to examine the potential protective impact of affluent neighborhoods on crime. Informed by social disorganization theory (Sampson and Groves, 1989), we included the percentage of lone-parent

families to capture the influence of family disruption on delinquency and crime. The specific descriptions of above variables are shown in Table 3.2.

### **3.3.3.2.2. Demographic Characteristics**

Several demographic characteristics of population including gender, age, race, marital status and mobility were examined in this study for their association with crime.

(1) Age structure and marital status: Drawing on routine activity theory, previous empirical studies have shown that individual characteristics including gender, age, race, and marital status influence individuals' routine activity patterns and thus their risk of involving in criminal incident as either victims or perpetrators. In particular, many studies indicated that males falling in the group aged 15-24 is at higher risk of both offending and victimization (Hirschi and Gottfredson, 1983; Land et al., 1990). In contrast, according to the 2004 General Social Survey (GSS), the group 65 or older was underrepresented in the total population with respect to victimization rates (Gannon and Mihorean, 2005). Besides, single people are found to be at greater risk of experiencing violence partially due to their propensity to participate in evening activities (Savoie, 2008a). Hence, we took the impact of age structure and marital status on crime into account by including the measures of percentage of males aged 15 to 24, percentage of population aged 65 years and over, and percentage of single persons (Table 3.2).

(2) Residential stability: In this study, residential stability was measured by two variables: percentage of owner-occupied dwellings and percentage of residents who lived at the same address five years earlier (Table 3.2). In comparison to resident mobility, residential stability help increase social interaction among neighbours and a collective commitment to the neighbourhood, thus contributing to the development of social control over criminal behavior

(Wallace et al., 2006). In addition, population density was included based on two theoretical possibilities derived from routine activity theory: population density tends to increase the number of offenders and potential victims in an area and thus provides more opportunities for crime, or oppositely, may increase the number of guardians in an area and thus have a negative relationship with crime rates (Cahill and Mulligan, 2007).

#### **3.3.3.2.3. Ethno-cultural Characteristics**

According to social disorganization theory (Shaw and McKay, 1942), a neighborhood's ethnic segregation and cultural heterogeneity influence crime to the extent that they are accompanied by diversity in terms of norms, languages and interests that might inhibit community cohesion (Elliot et al., 1996). In this study, three variables were used to capture the ethno-cultural composition in an area: percentage of Aboriginal population, percentage of visible minorities and percentage of recent immigrants (Table 3.2). In Canada, several studies have indicated that Aboriginal people are overrepresented in terms of both victimization and offending (Statistics Canada, 2001b). Visible minority groups were selected to measure ethno-cultural composition as they are more clearly defined than groups based on ethnic origin (Charron, 2009). It has been argued that initially immigration may impede integration into society, although this effect declines as the length of residence in the country increases (Breton, 2003). Recent immigrants might be more likely to face difficulties in social participation and consequently gain fewer resources (e.g., social capital) from social interaction within the community (Wallace et al., 2006). Given that immigrants make up a large proportion of population in many Canadian cities, the potential effect of immigrants on crime was considered by a measure of the percentage of residents who immigrated to Canada in the last decade.

#### **3.3.3.2.4. Dwelling characteristics**

According to broken window theory (Kelling and Coles, 1996), once the physical environment of a place becomes deteriorated, it undermines the willingness and ability of residents to enforce social order, which allows further deviancy and crime to occur. Therefore, percentage of dwellings that require major repairs, percentage of dwellings built before 1961 were included to partially measure disadvantaged dwelling conditions and according physical disorder in a neighbourhood (Table 3.2).

#### **3.3.3.3. City-level Independent Variables**

A number of social, economic and demographic features of city have proven to be associated with crime, such as median family income, unemployment, divorced rate, single-parent family, percent young, percent Black population, and population size/density (Land et al., 1990; McCall et al., 2007). However, a small sample size of six cities restricted the number of city-level variables that could be simultaneously included in the multilevel models. Therefore, we focused on two city-level variables (Table 3.2): First, city population (in 2001) was included to capture the potential effect of city size on neighbourhood-level crime rates. Researchers in sociology have long underscored the importance of urbanization (e.g., urban population growth) on human behavior, such as increasing the level of anonymity, tolerance and alienation that may further lead to increasing deviant impulses and weakening social control of misbehaviour (Wirth, 1938). Moreover, a growing population may contribute to interpersonal exchanges and thus increase opportunities for interpersonal conflict, including crime (McCall et al., 2007). Many cross-sectional city-level crime studies revealed a positive association between crime rate and city population (e.g., Land et al. 1990; McCall et al. 1992; Sherman, 1992; Weisburd and Green,



1994). Second, population per police officer was included as an indication of the public social control exerted by city police forces. This variable shows advantage over the total number of police officers, since it measures available police resources in a city while taking the underlying population into account. It is hypothesized that population per police officer has a deterrence effect on crime by raising the probability of being apprehended (Sampson and Cohen, 1988).

Descriptive statistics for the dependent variable (violent and property crime rates) and neighbourhood- and city- level independent variables are shown in Appendix A.1

## **Chapter 4 Methodology**

In order to investigate the spatial patterns of crime and explore their relationships to the underlying social contexts, the quantitative methodology employed in this study was a combination of exploratory spatial data analysis (ESDA) and multivariate analysis using multilevel modelling and spatial regression techniques. More specifically, we began with an ESDA approach as an initial step for visualizing spatial patterns and testing for spatial dependence in the crime data. The results of the ESDA informed our multilevel analyses, wherein we assessed the effects of both neighbourhood- and city-level characteristics on neighbourhood crime rates, with adjustments for spatial dependence. The details about each step are described in the following sections.

### **4.1. Exploratory Spatial Data Analysis**

The first step in our spatial analysis was to examine the spatial distribution of crime rate across neighbourhoods within the six Canadian cities under study. Given the limited knowledge of the crime data under study, our analysis was conducted within the exploratory data analysis (EDA) paradigm and using an exploratory spatial data analysis (ESDA) approach in particular (Messner et al., 1999). EDA provides essential first insights into the structure of a dataset and specifically, it is “a collection of descriptive and graphical statistical tools intended to discover patterns in data and suggest hypotheses by imposing as little prior structure as possible” (Tukey, 1977). Exploratory spatial data analysis (ESDA) is an extension of exploratory data analysis (EDA) that focuses explicitly on spatial aspects of data, describing and visualizing spatial distribution, identifying atypical locations or spatial outliers, detecting patterns of spatial association, clusters or hot spots, and suggesting spatial regimes or other forms of spatial heterogeneity (Anselin,

1994). The ESDA approach applied in this study was implemented in GeoDa, which is a free-domain software package that includes an extensive range of functionality from simple mapping to exploratory data analysis, the visualization of global and local spatial autocorrelation, and spatial regression (Anselin, 2003a). Specifically, a two-step process was followed in conducting the ESDA: data visualization and spatial autocorrelation analysis.

#### **4.1.1. Data Visualization**

The first step in our ESDA involved the use of mapping and display functionality in GeoDa to visualize crime distribution in the six Canadian cities. In particular, GeoDa provides an interactive environment that combines maps with statistical graphics, using the technology of dynamically linked windows (Anselin, 2003a). In this study, box maps and box plots were dynamically linked to interactively describe the general spatial distribution of crime rates across neighbourhoods (CTs/DAs) of interest.

Box map is a quartile map in which observations (e.g., crime rate) are classified into six categories: four quartile ranges (1-25%, 25-50%, 50-75%, and 75-100%) and two outlier groups at the low and high extremes of the distribution. Box plot is used as a simple device to characterize the cumulative distribution and identify outliers as well (Anselin and Bao, 1997). In this study, an observation (crime rate) was defined as an outlier if it lies above the upper boundary of the interquartile range by an amount that is at least 1.5 times the value of the interquartile range.

#### **4.1.2. Spatial Autocorrelation Analysis**

Box maps and box plots provide a first insight into the spatial structures of a dataset in terms of describing spatial distribution and spatial outliers. However, the visual inspection of maps based

on human perception is not sufficiently rigorous to identify significant spatial clustering in the data and therefore needs to be further verified with formal tests and tools (Messner et al., 1999). Therefore, the visualization process was followed by assessing global and local patterns of spatial autocorrelation by means of the Moran's I statistic and its local counterpart (local Moran's I). As noted earlier, spatial autocorrelation is defined as "the coincidence of similarity in value with similarity in location" (Anselin, 1988). Spatial autocorrelation can be further classified as either positive or negative. Positive spatial autocorrelation refers to a situation where similar values tend to cluster in space, while negative spatial autocorrelation exists when dissimilar values appear in close geographical locations (Le Gallo and Ertur, 2000).

In this study, global autocorrelation was assessed based on the Moran's I statistic, which is the most widely known measure of spatial dependence for its wide applicability to both point and polygon data (Cliff and Ord, 1981; Upton and Fingleton, 1985; Haining, 2003). The global Moran's I<sup>2</sup> (Cliff and Ord, 1981) provides an global indication of the extent to which the spatial pattern of the entire dataset is compatible with a null hypothesis of spatial randomness, under which the values at one location do not depend on values at other locations (Messner et al., 1999). Rejection of this null hypothesis thus suggests an overall spatial dependence of the data under investigation (Sridharan et al., 2007). As described by Baller et al. (2001), "a significant and positive value of this statistic indicates spatial clustering (contagion, spillovers, externalities), whereas a significant and negative value suggests a checkerboard pattern of values (competition, repulsion)". Implemented in GeoDa software, significance of the Moran statistic is tested by

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<sup>2</sup> The global Moran's I is defined as  $I = \frac{\sum_i \sum_j W_{ij} (y_i - \mu)(y_j - \mu)}{\sum_i (y_i - \mu)^2}$  where  $W_{ij}$  is an element of a row-standardized spatial weights matrix,  $y_i$  is the crime rate for neighbourhood  $i$ ,  $y_j$  is the crime rate for neighbourhood  $j$ , and  $\mu$  is the average crime rate in the sample (more details, see Cliff and Ord, 1981).

comparison to a reference distribution generated by random permutations of the observed values (Sridharan et al., 2007).

One of the core concepts involved in the spatial autocorrelation analyses is the definition of “neighbours”, which can be operationalized by means of a spatial weight matrix (Sridharan et al., 2007). As described in Anselin (1998), “a spatial weights matrix contains a row for each observation in which the non-zero elements (typically equal to one) stand for the neighbours” (Anselin, 1998). Such neighbours can be defined in a number of ways either based contiguity (sharing a common boundary) or distance criteria (within a given critical distance of each other (Anselin, 1998). Specifically, contiguity can be further divided as either “rook” contiguity (only pure borders) or “queen” continuity (both borders and common vertices) (Sridharan et al., 2007). In this study, since our focus was on the crime rates of CTs/ADs that are naturally connected through the boundaries, the choice of a simple first-order contiguity was appropriate for it is the most direct way to ensure no “islands” are present in the data (each CT/AD is connected with at least one other CT/AD). The rook contiguity matrix was conducted initially as it is stricter and exclusive in terms of statistics analysis while the robust of the results was further checked using the queen continuity. By this method, CTs/ADs with a common boundary were considered as neighbours and tended to have potential influences on each other.

The Moran’s I can be visualized through the Moran scatterplot in which the spatially lagged values of variable (weighted average of values at neighbouring locations) is plotted against the original value of that variable at each location. The slope of the linear regression line through the scatterplot corresponds to the value of the global Moran’s I for spatial autocorrelation. The steeper the slope, the stronger is the degree of autocorrelation (Anselin, 1998). More importantly, the Moran scatterplot provides an easy way to divide the nature of spatial autocorrelation into

four categories, corresponding to spatial clusters (positive spatial autocorrelation) and spatial outliers (negative spatial autocorrelation) (Anselin, 1998). Specifically, observations in the lower left (low-low) and upper right (high-high) quadrants represent potential spatial clusters in a sense that a location is surrounded by locations with similar values. In contrast, observations in the upper left (low-high) and lower right (high-low) quadrants suggest potential spatial outliers with high values surrounded by low values and vice versa (Sridharan et al., 2007).

The global Moran's I provides a measure of the overall spatial autocorrelation, however, it is not able to indicate "where the clusters or outliers are located, nor what type of spatial correlation is most important (e.g., correlation between high or between low values)" (Anselin et al., 2007). To address this problem, the Local Indicators of Spatial Association (LISA) developed by Anselin (1995) provide a local measure of spatial autocorrelation for each specific location and help identify the type of spatial association (e.g., positive vs. negative) (Sridharan et al., 2007). In this study, the local spatial autocorrelation was assessed by means of the Local Moran's I statistic and the so-called LISA cluster map. The local Moran's I statistic<sup>3</sup> assesses a null hypothesis of spatial randomness by comparing the values in each location to values in neighbouring locations (Messner et al., 1999). Rejection of this null hypothesis indicates significant spatial autocorrelation around the particular location under examination. In this study, the significance of the local Moran statistic was determined by generating a reference distribution using 999 random permutations (Sridharan et al., 2007). Moreover, the LISA cluster map combines information from the Moran scatterplot and the Local Moran's I statistic, showing the locations with significant Local Moran's I and indicating by a color code the quadrant (i.e., high-high,

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<sup>3</sup> The local Moran's I is defined as  $I_i = \frac{(y_i - \mu)}{\sum (y_i - \mu)^2} \sum_j W_{ij} (y_j - \mu)$

where  $W_{ij}$  is an element of a row-standardized spatial weights matrix,  $y$  is the crime rate, and  $\mu$  is the average crime rate in the sample (Anselin, 1995).

low-low, high-low and low-high) in the Moran scatterplot to which that location belongs (Anselin and Bao, 1997).

In brief, ESDA is a critical first step for detecting spatial patterns, spatial regimes and diagnosing possible misspecification in analytic models (Baller et al., 2001). However, it is not able to explain the spatial patterns observed in crime rates. In this sense, ESDA as such is not an end in itself and it represents the exploratory phase of research that provides a rigorous basis for a model specification that can be used in the next stage of the analysis (Messner et al., 1999).

## **4.2. Multilevel Analysis**

### **4.2.1. Rationale for Multilevel Analysis**

Since the data consist of a two-level hierarchy with neighbourhoods nested within cities, multilevel modelling techniques were used to examine the influences of both neighbourhood- and city-level characteristics on neighbourhood violent and property crime rates. Multilevel modelling has become the standard method for estimating contextual effects when individuals are clustered within social groups (e.g., school) or geographic areas (e.g., neighbourhood, city country etc.), and can also be applied to situations where smaller areas are nested within regions or larger areas (Diez-Roux, 2000). These models not only allow simultaneous examination of multiple social contexts (instead of solely neighbourhood) in shaping spatial distributions of crime, but also overcome the methodological limitations inherent in traditional single-level analyses. Therefore, the use of multilevel modelling in this study was appropriate, particularly for the following reasons.

Statistically, multilevel models adequately account for the dependence among observations from the same group or context to produce more accurate parameter estimates and standard errors

(Raudenbush and Bryk, 2002). In this study, neighbourhoods within a particular city may be more similar to one another compared to neighbourhoods in another city and, therefore, may not constitute independent observations. The interdependence of neighbourhoods violated the assumption of traditional regression models (e.g., OLS) that observations are independent and error terms are uncorrelated. The failure to account for nonindependence of observations may result in standard errors that are biased downward and increase the change of Type I error (Hox and Kreft, 1995); consequently the inferences regarding the effects of independent variables may be misleading. By contrast, the potential interdependence between neighbourhoods was explicitly controlled in multilevel models in which both between- and within-city (neighbourhood) levels were specified and the corresponding equation was estimated simultaneously.

Furthermore, multilevel models permit a partitioning of the variance of a given outcome (i.e., crime rates) into different levels of analysis to allow separate estimation of the effects at each level. In this study, the hypotheses on crime and social contexts at both the city and neighbourhood levels were tested within a multilevel design. We were able to estimate the amount of variation in neighbourhood crime rates that was attributed to between cities versus differences between neighbourhoods. We were also able to disentangle the impact of two different social contexts (neighbourhood vs. city) on the geographic distribution of crime. A more rigorous conclusion would be given of which factors at which ecological level (neighbourhood vs. city) can account for the observed variation in crime rates, after controlling for the confounding effects of other factors at another level.

In summary, by using a multilevel modeling approach, several research questions regarding the relationships of violent and property crime rates to neighbourhood-level and city-level



characteristics can be investigated: (1) Do neighbourhood crime rates vary significantly across the six Canadian cities? (2) How much of the variation in crime rates between neighbourhoods can be attributed to the socioeconomic, demographic and dwelling features of neighbourhoods, while controlling for city random effects? (3) Does the spatial dependence of neighbourhoods influence the effects of neighbourhood contextual variables on crime rates? (4) To what extent do city characteristics affect neighbourhood-level crime rates, above and beyond the characteristics of neighbourhoods within them? (5) To what degree can the between-city variance in neighbourhood crime rates be explained by the neighbourhood- and city-level characteristics as well as the spatial dependence of neighbourhoods?

## **4.2.2. Model Specification**

### **4.2.2.1. The Rationale of Hierarchical Linear Models**

Hierarchical linear modelling procedures (Raudenbush and Bryk, 2002) realized through HLM7 software (Raudenbush et al., 2000) were used to estimate the dependent variables (i.e., violent and property crime rates) as a linear function<sup>4</sup> of neighbourhood- and city-level characteristics (for detailed explanations of these models, see Raudenbush and Bryk, 2002). Specifically, the hierarchical linear models consisted of two equations estimated simultaneously, in which neighbourhood-level variation within each city was explained by a neighbourhood-level equation (level-1) and the variation across cities in the city-specific regression coefficient (i.e., intercept) was explained by a city-level equation (level-2). General equations for the two-level models are presented in Figure 4.1.

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<sup>4</sup> We assumed the dependent variables (violent and property crime rates) are continuous and approximately normally distributed at each value of continuous independent variables (neighbourhood- and city-level characteristics).

At level 1, the neighbourhood-level equation is:

$$Y_{ij} = \beta_{0j} + \sum_{p=1}^P \beta_p X_{pij} + \varepsilon_{ij} \quad (\text{Eq.4.1})$$

- $Y_{ij}$  is the violent/property crime rate for neighbourhood  $i$  in city  $j$ ;
- $X_{pij}$  is the value of neighbourhood-level variable  $X_p$  for neighbourhood  $i$  in city  $j$ ;
- $\beta_{0j}$  is the city-specific intercept, the mean value of neighbourhood crime rates in city  $j$ ;
- $\beta_p$  is the regression coefficient of neighbourhood-level variable  $X_p$  ( the main effect of  $X_p$  which is fixed or constant across all the cities)
- $\varepsilon_{ij}$  is the neighbourhood-level random effect that represents the deviation of neighbourhood  $i$ 's outcome from the predicted outcome based on the values of  $X_p$ . This residual is assumed to be independent and normally distributed within each city, with a mean of 0 and a variance of  $\sigma^2$ .

At level 2, the city-level equation is:

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^Q \gamma_{0q} Z_{qj} + \delta_{0j} \quad (\text{Eq.4.2})$$

- $\gamma_{00}$  is the overall intercept;
- $\gamma_{0q}$  is the main effect of  $Z_q$  (averaged over all cities in the population);
- $\delta_{0j}$  is a city-level random effect that represents the unique deviation of the intercept of city  $j$  from the overall intercept  $\gamma_{00}$  after accounting for the effect of  $Z_q$ ; it is the city-level residual assumed to be independent from the neighbourhood-level residuals  $\varepsilon_{ij}$  and have a normal distribution with mean 0 and a variance of  $\tau_{00}$

These submodels are combined into an overall estimation of crime rates as follows:

$$Y_{ij} = \gamma_{00} + \sum_{p=1}^P \beta_p X_{pij} + \sum_{q=1}^Q \gamma_{0q} Z_{qj} + \delta_{0j} + \varepsilon_{ij} \quad (\text{Eq.4.3})$$

**Figure 4.1** - General equations for a two-level hierarchical linear model

The specification of the hierarchical model in Eq.4.3 is incomplete without specifying the assumptions concerning the errors at each level in the model:

- (1) Each level-1 residual  $\varepsilon_{ij}$  is independently and normally distributed with a mean of 0 and variance  $\sigma^2$  for each city, that is  $\varepsilon_{ij} \sim N(0, \sigma^2)$
- (2) The neighbourhood-level explanatory variables  $X_{pij}$  are independent of  $\varepsilon_{ij}$  (i.e.,  $\text{Cov}(X_{pij}, \varepsilon_{ij}) = 0$  for all  $p$ )
- (3) The level-2 residuals ( $\delta_{0j}$ ) are independent between cities and have a normal distribution with a mean of 0 and a constant variance of  $\tau_{00}$
- (4) The city-level explanatory variables  $Z_{qj}$  are independent of  $\delta_{0j}$  (i.e.,  $\text{Cov}(Z_{qj}, \delta_{0j}) = 0$  for all  $q$ )
- (5) The residuals at level 1 and level 2 are independent (i.e.,  $\text{Cov}(\varepsilon_{ij}, \delta_{0j}) = 0$ )
- (6) The explanatory variables at each level are not correlated with the random effects at the other level (i.e.,  $\text{Cov}(X_{pij}, \delta_{0j}) = 0$  for all  $p$ ,  $\text{Cov}(Z_{qj}, \varepsilon_{ij}) = 0$  for all  $q$ )

The model defined in Eq.4.3 is one form of the random intercept models since only the level-1 intercept (i.e.,  $\beta_{0j}$ ) is allowed to vary randomly across cities while the slope (i.e.,  $\beta_p$ ) is modeled as fixed<sup>5</sup>. In brief, the model characterizes the distribution of neighbourhood crime rates in two parts: (a) a fixed part that is unchanged across cities, including the overall intercept (i.e.,  $\gamma_{00}$ ), the main effects of neighbourhood-level factors (i.e.,  $\beta_p$ ) and city-level factors (i.e.,  $\gamma_{0q}$ ), as well as (b) a random part, the composed error term that consists of the neighbourhood-level residual ( $\varepsilon_{ij}$ ) and the city-level residual ( $\delta_{0j}$ ). Denote the composed error term as  $\mu_{ij} = \delta_{0j} + \varepsilon_{ij}$  (Eq.4.4), then the residual variance is,

$$\text{Var}(\mu_{ij}) = \text{Var}(\delta_{0j} + \varepsilon_{ij}) = \tau_{00} + \sigma^2 \quad (\text{Eq.4.5})$$

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<sup>5</sup> It would be theoretically interesting to examine whether the relationships between neighbourhood-level predictors and crime rates vary across the cities by allowing the level-1 slopes to vary randomly across the cities as specified in Equation. However, the small sample size at level two (N=6) was not large enough for such an analysis.

The hierarchical model allows quantification of variance at different levels: the residual variances,  $\sigma^2$  and  $\tau_{00}$ , represent the within-and between-city variance in neighbourhood crime rates, respectively, that is left unexplained by the set of independent variables in the model. Furthermore, the errors for neighbourhoods nested in the same city are correlated, since  $\delta_{0j}$  is common for neighbourhoods within each city. Hence, for neighbourhood  $i$  and  $i'$  ( $i \neq i'$ ), the correlation of their error terms is:

$$\rho(Y_{ij}Y_{i'j}) = \frac{\text{Cov}(\mu_{ij}, \mu_{i'j})}{\sqrt{\text{var}(\mu_{ij})\text{var}(\mu_{i'j})}} = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \quad (\text{Eq.4.6})$$

This ratio is widely referred to as the *intra-class correlation coefficient* (ICC) (Raudenbush and Bryk, 2002). It estimates the proportion of the total variance in the outcome variable, neighbourhood violent/property crime rates, that is between cities after controlling for the set of independent variables. It also serves as an indicator of the degree of dependency among neighbourhoods that are nested in the same city: the more they are similar, the higher the intra-class correlation will be (Kreft and De Leeuw, 1998).

Possible ICC values range from 0 to 1 where a value less than 0.5 indicates that there is greater variability within cities than between cities, and a value greater than 0.5 shows that there is greater variability between cities than within them. An ICC value of 0 indicates that there is little or no variance between cities in the outcome variable (i.e., neighbourhood violent/property crime rates) after accounting for the independent variables in the model. In this case, the city-level residual term (i.e.,  $\delta_{0j}$ ) can be estimated as zero and the hierarchical linear model in Eq.4.3 reduces to a conventional fixed-effect regression model<sup>6</sup> including both neighbourhood-level and city-level independent variables (a model with no random effects, where all regression

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<sup>6</sup>  $Y_{ij} = \gamma_{00} + \sum_{p=1}^P \beta_p X_{p ij} + \sum_{q=1}^Q \gamma_{0q} Z_{qj} + \varepsilon_{ij}$

coefficients are modeled as fixed with no random component specified at the city level). Otherwise, exclusion of the city-level residual term a priori is inappropriate since it is unlikely that we can specify all the factors possibly responsible for the between-city variance in the outcome.

As the nonindependence of observations within groups (i.e., neighbourhoods within cities) violates the assumption underlying standard regression models (e.g., OLS), special estimation methods should be used to estimate the parameters in the hierarchical linear models (Diez-Roux, 2000). In this study, the parameters of the above equations (fixed effects, random effects, variances components) were estimated by means of full maximum likelihood available in HLM7. Using this approach, the variance-covariance parameters (i.e.,  $\tau_{00}$ ) and fixed effects (i.e.,  $\gamma_{0q}$ ) are estimated by maximizing their joint likelihood.

#### **4.2.2.2. Statistical Tests and Inferences**

A variety of hypothesis tests for fixed effects and variance components were implemented in this study using HLM7 software. Specifically, t-tests are provided for each of the fixed-effects coefficients (i.e.,  $\gamma$ 's), where a significant t-test value indicates that the parameter is significantly different from zero. This is a direct test of the hypothesis regarding the main effects of neighbourhood-level variables ( $\gamma_{p0}$ ) and city-level variables ( $\gamma_{0q}$ ) on neighbourhood-level crime rates. Chi-square tests are provided for the level-2 residual variance in intercepts (i.e.,  $\tau_{00}$ ) indicating whether this residual variance significantly differs from zero. This test statistic suggests whether cities differ significantly in average neighbourhood crime rates (after controlling for the neighbourhood- and city-level factors).

In addition to these statistical tests, HLM7 also provides a deviance statistic, defined as minus twice the log-likelihood of the model, for each model estimated. The deviance provides a measure of lack of fit between model and data. Generally, the larger the deviance, the poorer the fit of the model to the data. It is used to compare the overall fit of two alternative models applied to the same data (Snijders and Bosker, 1999). For example, suppose two models,  $M_0$  and  $M_1$ , are applied to one dataset, with  $M_0$  having  $m_0$  parameters and  $M_1$  having  $m_1$  parameters ( $M_1$  is assumed to be an extension of  $M_0$  with  $m_1 - m_0$  parameters added). For each model, a deviance statistic is computed, denoted as  $D_0$  and  $D_1$ . Differences between the deviances ( $D_0 - D_1$ ) can be used as a likelihood-ratio test having a chi-square distribution with degrees of freedom equal to the difference in the number of parameters estimated ( $m_1 - m_0$ ) (Snijders and Bosker, 1999). It indicates that whether one model is a significant improvement over another compared to the degree of freedom lost (e.g.,  $m_1 - m_0$ ). As suggested by De Leeuw and Kreft (1998), “in order to reach the conclusion that one model is a significant improvement over another, the difference in deviances between two models should be at least twice as large as the differences in the number of estimated parameters” (De Leeuw and Kreft, 1998, pp. 65).

Finally, an index of proportion of variance explained for the outcome variable at one or more levels (pseudo  $R^2$ ) was used to assess the degree to which within- and between-city variance in terms of neighbourhood crime rates that can be explained by neighbourhood-level and city-level variables. This concept is analogous to the multiple correlation coefficient ( $R^2$ ) in the traditional linear regression, which is interpreted as the proportion of variance in the dependent variable that is explained by the explanatory variables in the model (the squared correlation between the predicted and actual values of the dependent variable) (De Leeuw and Kreft, 1998). The difference is, however, in a single level analysis, only one source of variance present and

consequently only one  $R^2$  is calculated. As our hierarchical models involved two levels of analysis, two potential sources of variance can be explained by the explanatory variables: within-city and between-city variance. The variance explained at a particular level of analysis can be calculated by comparing the estimated residual variance at that level from a fitted model with the corresponding estimate from some base or reference model (Raudenbush and Bryk, 2002). In this study, the reference model chosen for computing these statistics was the null model without any explanatory variable. The estimates of level-1 and level-2 residual variance from a null model respectively represent the total within- and between- city variance in the outcome variable. Therefore, they can be used as a baseline to indicate how much reduction in variance takes place in one or both parts, when explanatory variables and/or random components are added to the models (Kreft and De Leeuw, 1998). Specifically, we denote the estimates for the level-1 residual variance as  $\sigma^2$  and the estimates for the level-2 residual variance in level-1 intercepts (i.e.,  $\beta_{0j}$  in Eq.4.2) as  $\tau_{00}$ . Thus, the variance explained at each level of analysis can be calculated using the following equations:

Proportion of variance explained at level-1:

$$R_W^2 = \frac{\sigma^2(\text{null model}) - \sigma^2(\text{fitted model})}{\sigma^2(\text{null model})} \quad (\text{Eq.4.7})$$

This ratio represents the amount of the within-city variance in neighbourhood crime rates accounted for by the fitted model.

Proportion of variance explained at level-2 in  $\beta_{0j}$

$$R_B^2 = \frac{\tau_{00}(\text{null model}) - \tau_{00}(\text{fitted model})}{\tau_{00}(\text{null model})} \quad (\text{Eq.4.8})$$

This ratio indicates the proportion of the between- city variance in neighbourhood crime rates accounted for by the fitted model.

In summary, multilevel models (hierarchical linear models) provide a statistical tool that can appropriately capture the hierarchical structure of data and thus may produce less biased and more accurate results than those obtained from traditional single-level regression analysis ( e.g., OLS). In this study, the use of multilevel models offered unique insight into both within-city and between-city variance in the neighbourhood crime rates, as well as the relative contribution of neighbourhood-level and city-level characteristics to this variance.



## **Chapter 5 Exploratory Spatial Data Analysis (ESDA)**

We began our analysis by examining the spatial distributions of violent and property crime rates across neighborhoods within the six Canadian cities. Given the limited knowledge of the crime data under study, our analysis was conducted within the exploratory data analysis (EDA) paradigm and using an exploratory spatial data analysis (ESDA) approach in particular (Messner et al., 1999). EDA provides an essential first insight into the structure of a dataset. ESDA is an extension of EDA that focuses explicitly on spatial aspects of data, describing and visualizing spatial distribution, identifying atypical locations or spatial outliers, detecting patterns of spatial association, clusters or hotspots, and suggesting spatial regimes or other forms of spatial heterogeneity (Anselin, 1994, 1998; Haining, 2003). The techniques of ESDA applied in this study included the use of graphic and mapping techniques to interactively visualize crime distributions, and a spatial autocorrelation analysis to formally test for spatial dependence of crime rates at the neighbourhood level.

ESDA is a critical first step in the spatial analysis of crime for detecting spatial patterns and generating hypothesis based on observed patterns in the data. If crime rates under study are not significantly clustered in space (i.e., the hypothesis of spatial randomness cannot be rejected), then there is little support for a hypothesis of a location effect in the crime data. On the other hand, if spatial dependence is significantly present in crime rates, there may be some spatial process at work, such as diffusion, which is worthy of further inquiry. This may become the basis for more formal hypothesis constructs and model specification that can be used in a subsequent stage of analysis (e.g., multilevel regression analysis).

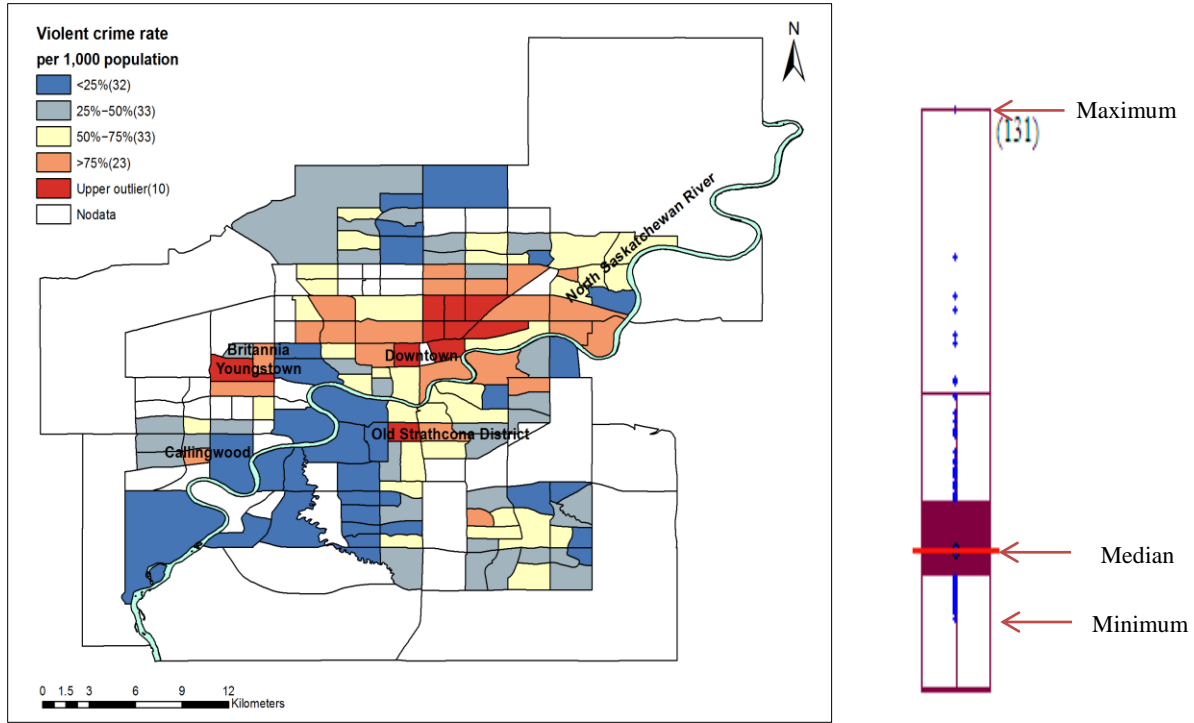
## 5.1. Spatial Patterns of Crime within Cities

The first step in our ESDA involved the use of maps and statistical graphics to visualize violent and property crime rates in six Canadian cities: Edmonton, Saskatoon, Halifax, Thunder Bay, Montreal and Toronto. A series of box maps and corresponding box plots (Figures 5.1-5.12) were generated for each city to illustrate the spatial distribution of violent and property crime rates across neighbourhoods. Box maps were used to show the location (quartile) of every neighbourhood (corresponding to CT or DA)<sup>7</sup> within the overall distribution of violent/property crime rates in a given city. Box maps group observations such as crime rates into six fixed categories: four quartiles (1-25%, 25-50%, 50-75%, and 75-100%) and two outlier groups at the low and high extremes of the distribution. Box plots show graphically the variation of crime rates based on the interquartile range (50%, 25% and 75% points in the cumulative distribution), as well as identifying extreme data outliers. In both the maps and the plots, “outlier” neighbourhoods are those CTs (DAs) with crime rates that fall significantly above the upper boundary of the interquartile range by an amount that is at least 1.5 times the value of the interquartile range (Anselin, 2005).

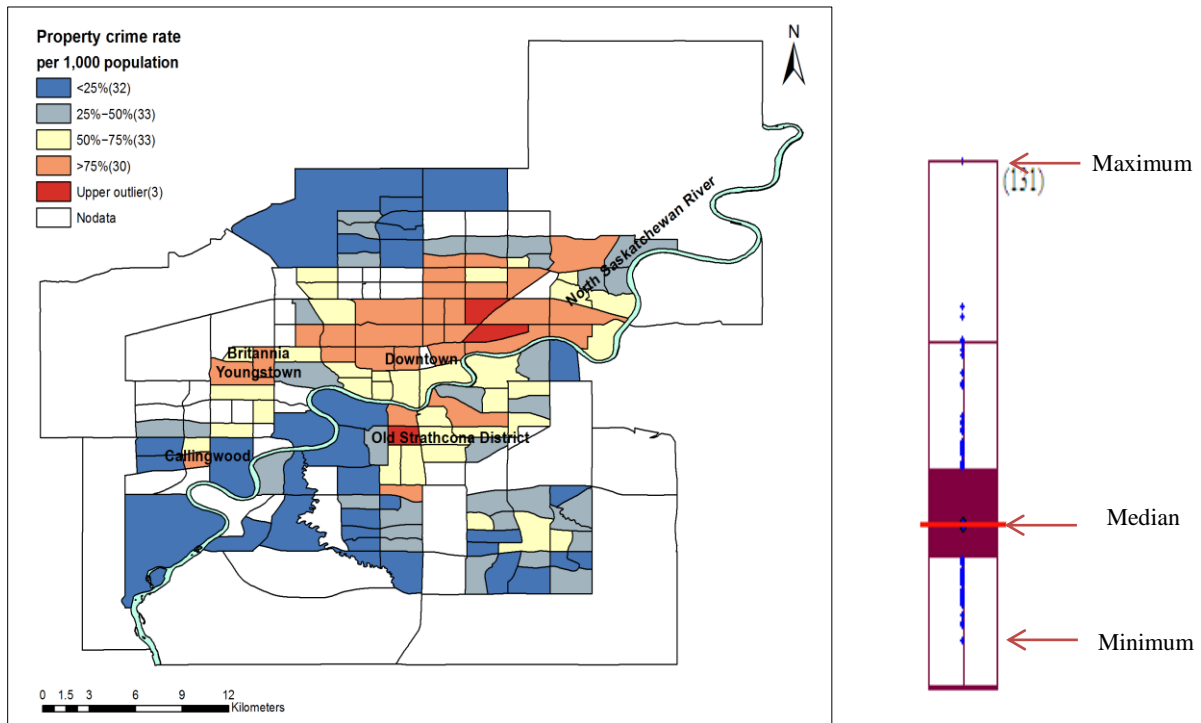
An overall examination of the box maps indicate that both violent and property incidents were not randomly distributed within the cities investigated, but were concentrated in a limited number of neighbourhoods. The analysis below describes the general trends in the spatial distributions of crime for each of the cities in this study. The main similarities and differences in the spatial patterns of crime among the cities are analyzed.

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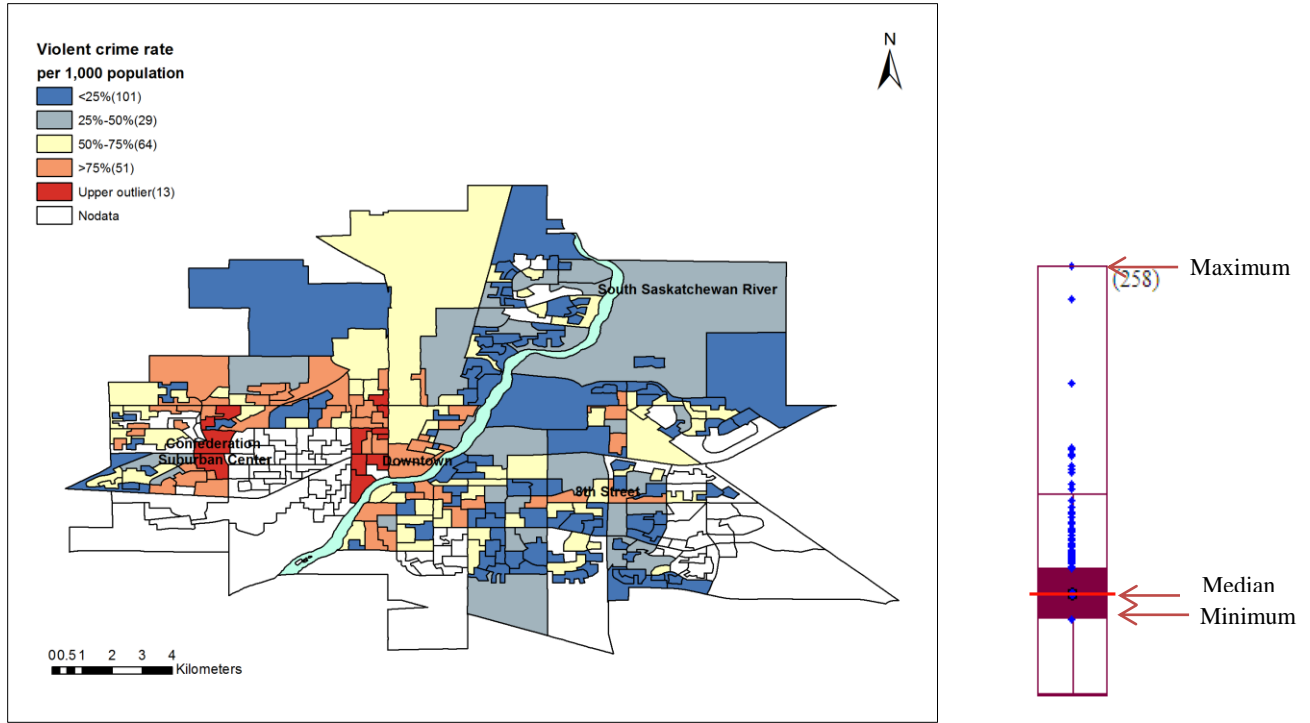
<sup>7</sup> According to the available dataset, the definition of neighbourhood corresponds to census tract (CT) in Edmonton, Halifax, Thunder Bay, Montreal and Toronto, whereas to dissemination area (DA) in Saskatoon.



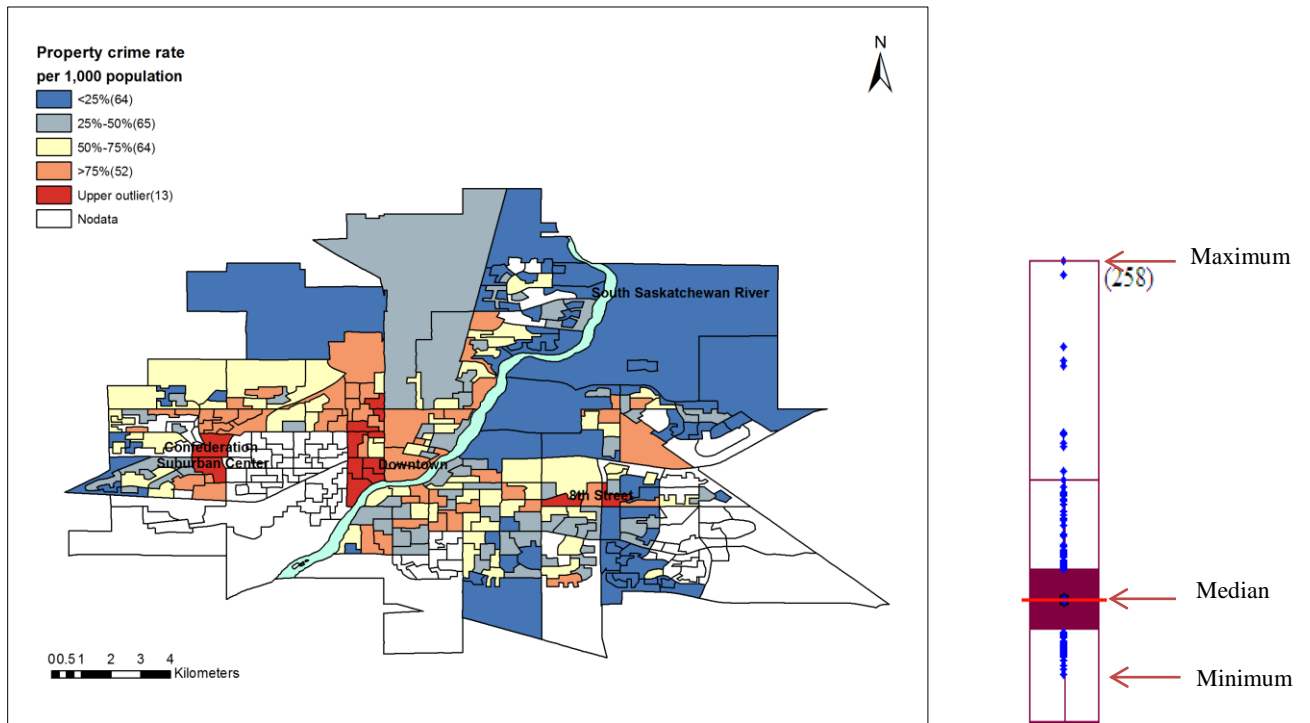
**Figure 5.1** - Box maps and corresponding box plot of violent crime rates (per 1,000 population) in 2001 in Edmonton CTs. A hinge of 1.5 was applied.



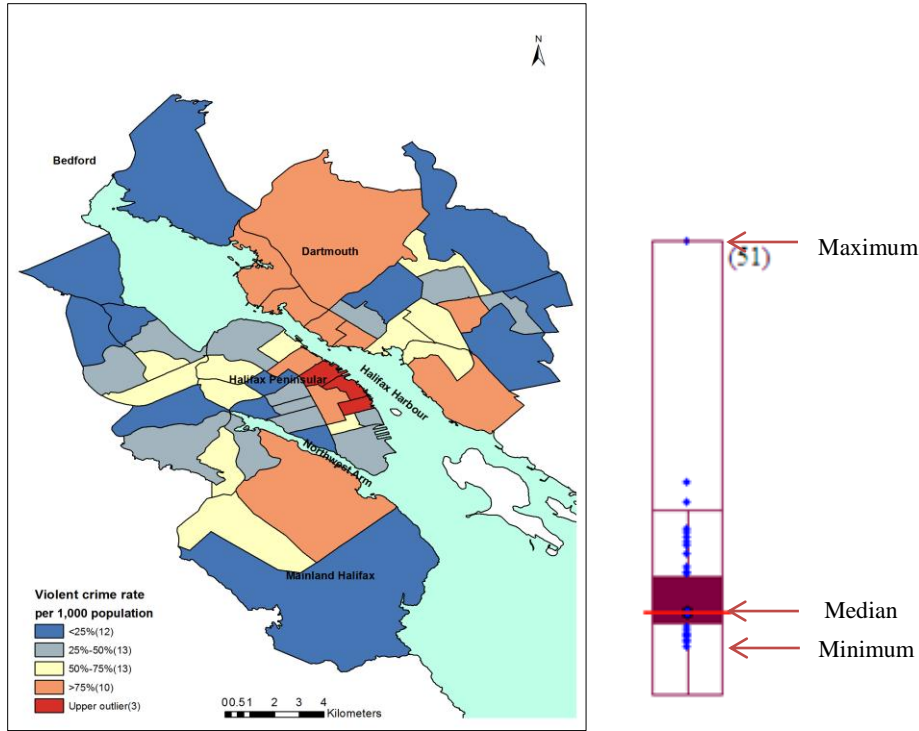
**Figure 5.2** - Box maps and corresponding box plot of property crime rates (per 1,000 population) in 2001 in Edmonton CTs. A hinge of 1.5 was applied.



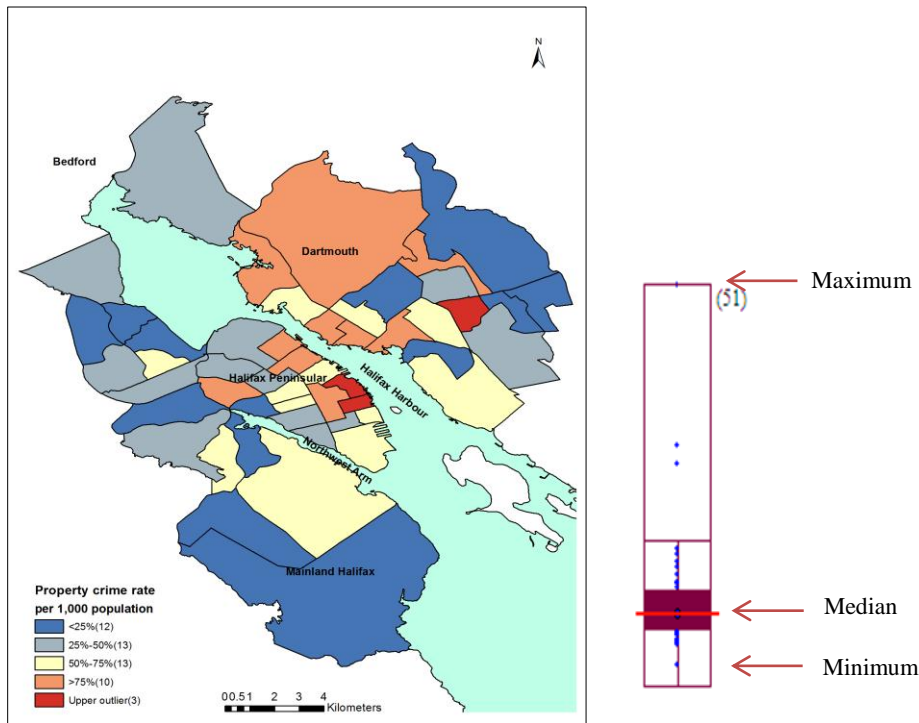
**Figure 5.3** - Box maps and corresponding box plot of violent crime rates (per 1,000 population) in 2001 in Saskatoon DAs. A hinge of 1.5 was applied.



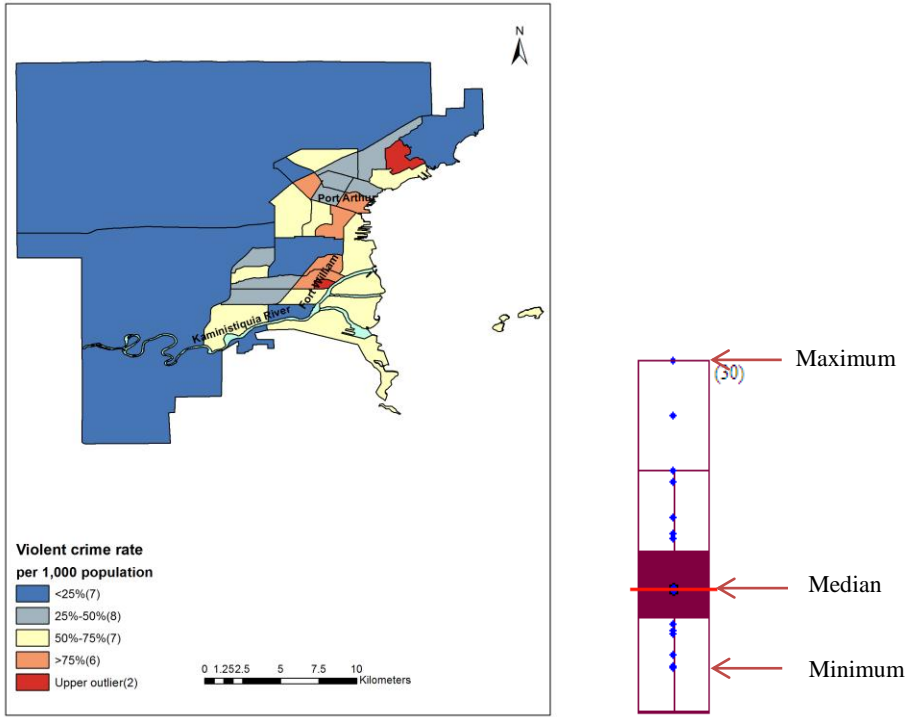
**Figure 5.4** - Box maps and corresponding box plot of property crime rates (per 1,000 population) in 2001 in Saskatoon DAs. A hinge of 1.5 was applied.



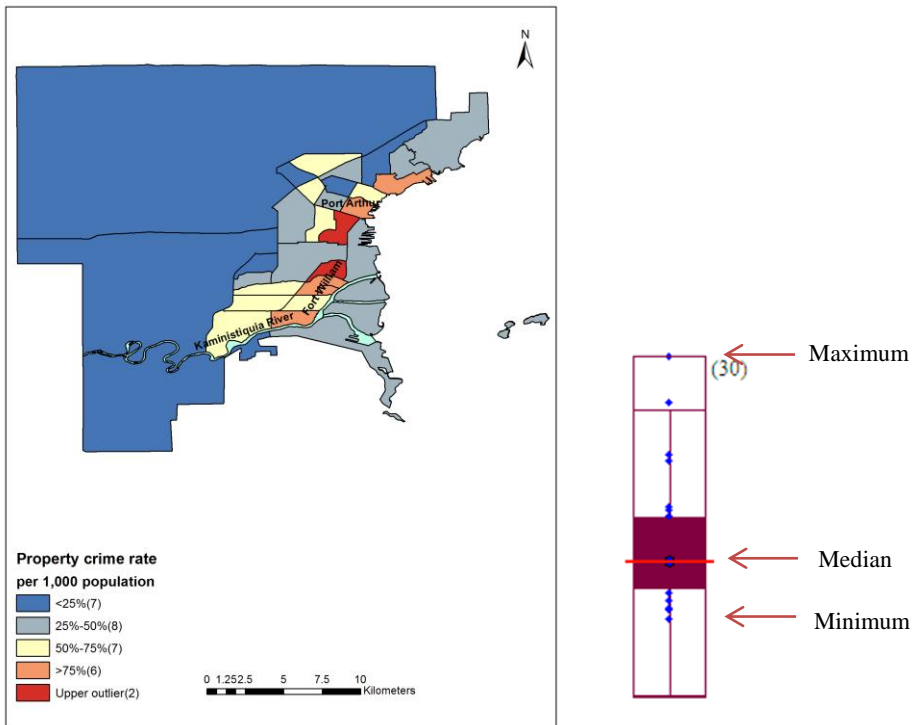
**Figure 5.5** - Box maps and corresponding box plot of violent crime rates (per 1,000 population) in 2001 in Halifax CTs. A hinge of 1.5 was applied.



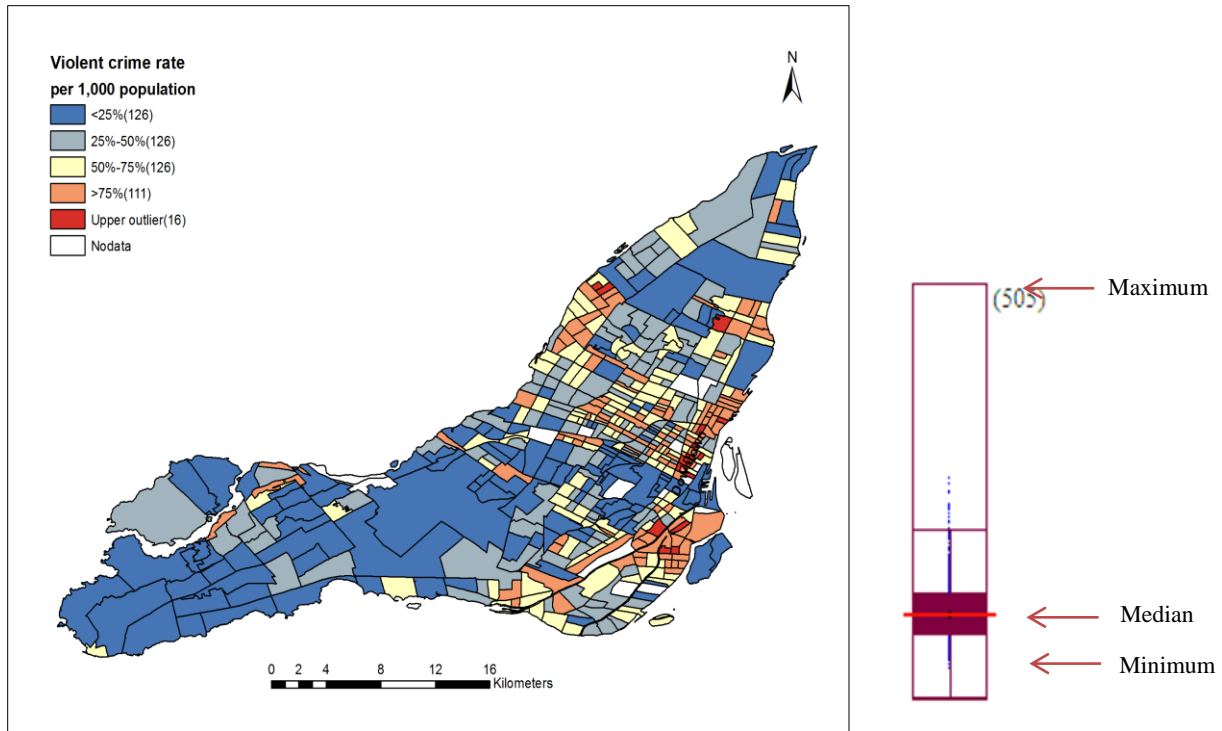
**Figure 5.6** - Box maps and corresponding box plot of property crime rates (per 1,000 population) in 2001 in Halifax CTs. A hinge of 1.5 was applied.



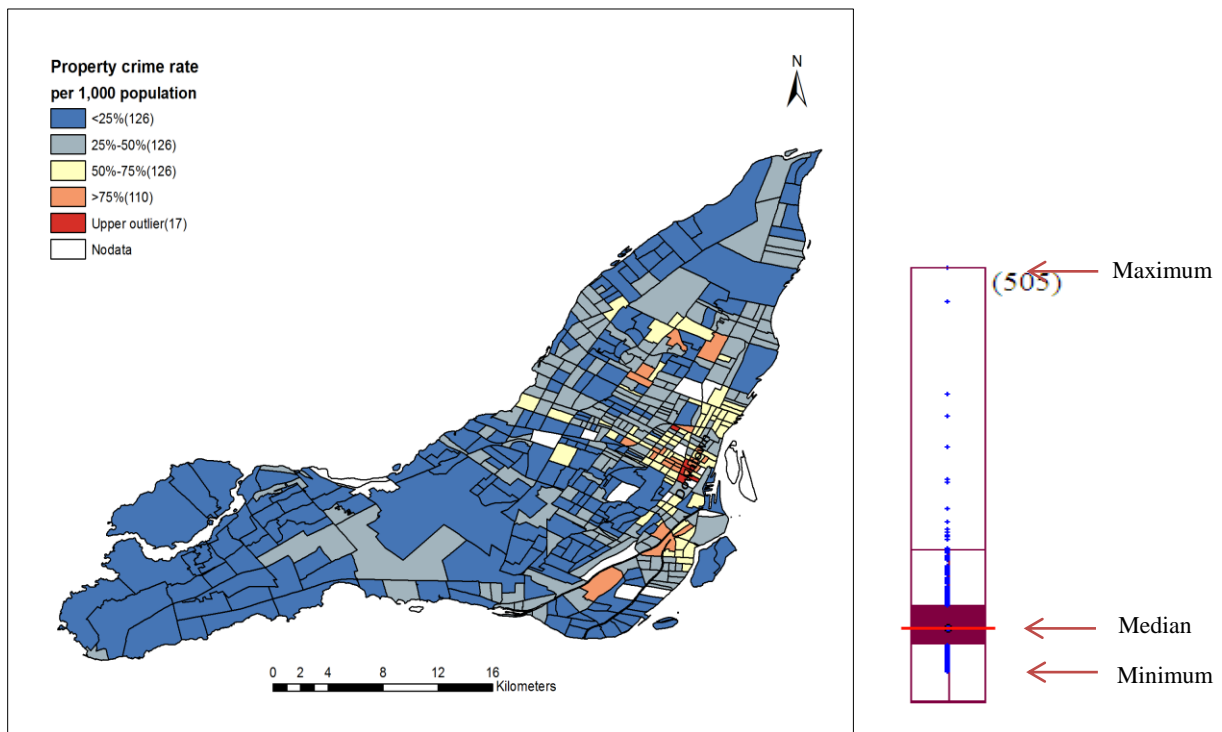
**Figure 5.7** - Box maps and corresponding box plot of violent crime rates (per 1,000 population) in 2001 in Thunder Bay CTs. A hinge of 1.5 was applied.



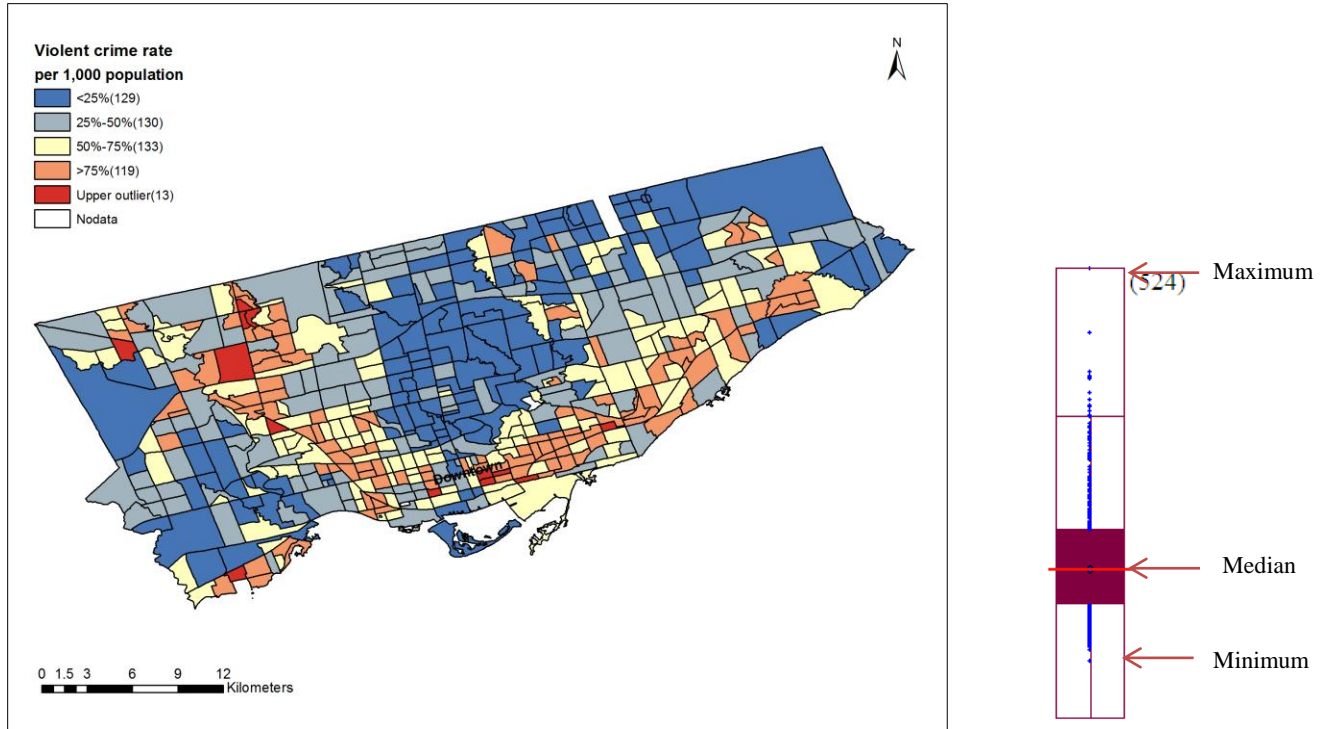
**Figure 5.8** - Box maps and corresponding box plot of property crime rates (per 1,000 population) in 2001 in Thunder Bay CTs. A hinge of 1.5 was applied.



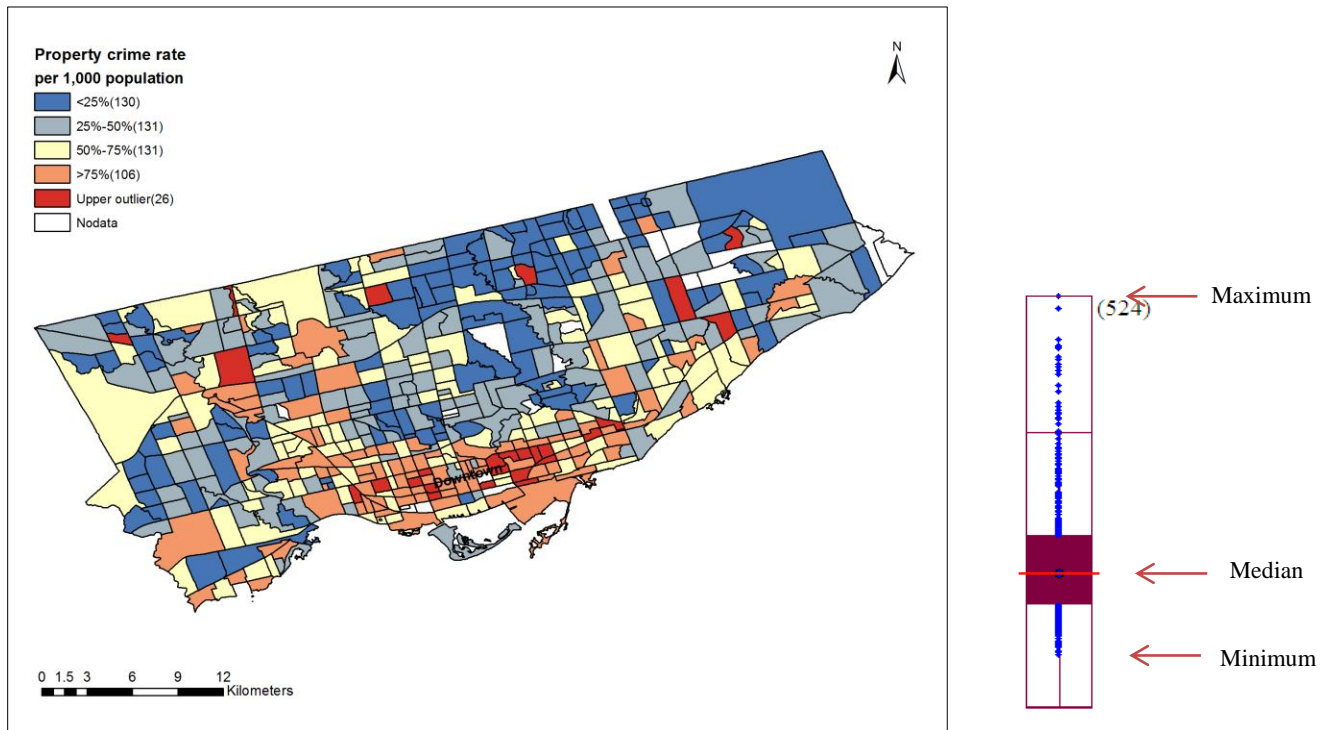
**Figure 5.9** - Box maps and corresponding box plot of violent crime rates (per 1,000 population) in 2001 in Montreal CTs. A hinge of 1.5 was applied.



**Figure 5.10** - Box maps and corresponding box plot of property crime rates (per 1,000 population) in 2001 in Montreal CTs. A hinge of 1.5 was applied.



**Figure 5.11** - Box maps and corresponding box plot of violent crime rates (per 1,000 population) in 2006 in Toronto CTs. A hinge of 1.5 was applied.



**Figure 5.12** - Box maps and corresponding box plot of property crime rates (per 1,000 population) in 2006 in Toronto CTs. A hinge of 1.5 was applied.



### **5.1.1. Spatial Distribution of Crime in the City of Edmonton**

Figures 5.1 and 5.2 display the box maps and box plots for the violent and property crime rates (2001) respectively across the 130 Edmonton census tracts (CTs). An examination of the box maps reveals that police-reported violent and property crime rates were not distributed uniformly within the City of Edmonton. The corresponding box plots identified 10 upper outlier CTs with extreme high violent crime rates and 3 upper outliers with elevated property crime rates. No lower outliers were identified for both types of crime. Generally speaking, violent crime and property crime rates exhibited similar spatial distributions in Edmonton, which were characterized by a north-south division: more crimes were likely to be reported north of the North Saskatchewan River than in the south, after controlling for the underlying population.

Moreover, both the highest violent and property crime rates (CTs corresponding to upper outliers and the fourth quartile) showed the highest concentrations in the downtown core and the neighbourhoods bordering it to the north, and moderate concentrations around certain large shopping malls in the Callingwood South and Britannia Youngstown neighbourhoods, all located on the north side of the North Saskatchewan River. A few exceptions were a small number of high crime neighbourhoods south of the river, located near the University of Alberta campus and Whyte Avenue in the Old Strathcona district. It seems that the crime hotspots in Edmonton tend to be associated with commercial and entertainment activity, as most of them corresponded to the city's major shopping centers (e.g., Mayfield Common Shopping Center), commercial streets (e.g., Whyte Avenue), and arts and entertainment district (e.g., the Old Strathcona district). The presence of higher crime rates around the university campus also implies that a large proportion of young people (mostly university students) along with overrepresentations of rented

accommodation might be a factor contributing to the spatial distributions of crime in those neighbourhoods.

On the other hand, the majority of the lowest violent and property crime rates (CTs in the first quartile) occurred in the southwestern peripheral areas. Some neighbourhoods in the north edge of the city also experienced fewer violent or property crimes. Such areas were mainly newly developed suburbs that are usually comprised of residential neighbourhoods.

### **5.1.2. Spatial Distribution of Crime in the City of Saskatoon**

The box map in Figure 5.3 illustrates the spatial distributions of violent crime rates (2001) across 258 neighbourhoods (DAs) in Saskatoon. In general, there was a noticeable presence of high violent crime rates in the urban core, located on the west side of the South Saskatchewan River. In fact, all of the 13 DAs with the highest violent crime rates (upper outliers) were located in the Riversdale and Caswell Hill neighbourhoods and the Confederation suburb center (the detailed Saskatoon neighbourhood map see Charron, 2008). The neighbourhoods bordering these areas to the north, as well as the downtown core (the Central Business District) showed the second highest violent crime rates (DAs in the fourth quartile). Although elevated crime rates were more concentrated in the western portion of the city, a small number of crime hotspots (DAs in the fourth quartile) also appeared on the east side of the South Saskatchewan River, including certain suburban neighbourhoods in the central-east (the neighbourhood of Sutherland), in the southeast (e.g., the Buena Vista, Queen Elizabeth neighbourhoods) and commercial areas adjacent to 8th Street. Apart from these small areas with high crime rates, however, the majority of neighbourhoods east of the South Saskatchewan River exhibited substantially lower violent crime rates. In fact, there were 101 neighbourhoods having no violent incidents during 2001 (DAs in the first quartile).

A box map and accompanying box plot for the property crime rates (2001) in Saskatoon are shown in Figure 5.4. Compared to violent offence, property crime rates were generally more dispersed across the Saskatoon neighbourhoods, although an identical number of upper outliers were identified (n=13). A number of high property crime rates neighbourhoods (>75%) were spread out in many areas of the city. Nonetheless, similar to violent crime rates, the property crime rates in Saskatoon showed an apparent contrast between the east and west sides of the South Saskatchewan River. Almost all the highest property crime rates (upper outliers) were concentrated in the Riversdale and Caswell Hill neighbourhoods and the Confederation shopping area, all of which were situated west of the South Saskatchewan River. One exception is two additional hot spots east of the South Saskatchewan River (the College Park and Greystone Heights neighbourhoods), bordering the 8th Street commercial strip. As with violent crime, property crime rates were particularly lower in outlying neighbourhoods situated in the northeast and southeast of the city.

In summary, both violent and property crime have highlighted the Riversdale, Caswell Hill neighbourhoods, and the Confederation suburban center as the highest crime areas in Saskatoon. Previous research indicated that the Riversdale and Caswell Hill neighbourhoods were comprised of populations with disadvantaged socioeconomic status, as evident in a large proportion of low income households, lone-parent families, low education attainment and high unemployment rates (more detailed see Charron, 2008). This finding follows social disorganization theory, which suggests that economic vulnerability of a neighbourhood's residents along with the resulting limited access to socioeconomic resources may compromise adherence to the behavioural norms endorsed by society, in general, and thus create a setting conducive to the perpetration of crimes (Massey, 1996; Body-Gendrot, 2001; Forrest and

Kearns, 2001; Bauder, 2002; Sampson et al., 2002; Charron, 2009). Moreover, the disadvantage characteristics of neighbourhoods may inhibit the establishment of strong social control of crime by the local community (Savoie, 2008b).

On the other hand, many crime hotspots in Saskatoon tend to be associated with concentrations of commercial and economic activities (e.g., shopping centres, commercial thoroughfare, employment hubs). Such examples include the downtown core, areas around the Confederation shopping center, those near 8th Street commercial strip and the Sutherland Industrial neighbourhood. These are areas of intense human activity, which according to routine activity theory, tends to bring together conditions favourable to crime, such as more potential offender and victims (Cohen and Felson, 1979).

### **5.1.3. Spatial Distribution of Crime in the City of Halifax**

Figures 5.5 and 5.6 display box maps and accompanying box plots showing the distribution of violent and property crime rates (2001) across 51 neighbourhoods (CTs) in the city of Halifax. The maps indicate that police-reported crime rates for both violent and property incidents were not evenly distributed across the city, but rather concentrated in certain neighbourhoods. An identical number of upper outliers ( $n=3$ ) were identified for violent and property crime rates, and the geographical distributions for these CTs were also similar. Figure 5.5 shows that the neighbourhoods with the highest violent crime rates were noticeably clustered in the downtown area, which is located on the eastern-central portion of the Halifax Peninsula on Halifax Harbour. To a lesser degree, some high violent crime neighbourhoods were located in the former city of Dartmouth and the southern part of Mainland Halifax bordering the Northwest Arm. Likewise, high-property crime rates (Figure 5.6) appeared on either side of Halifax Harbour, with a noticeable concentration in the downtown core and areas with large shopping centers in

Dartmouth (Savoie, 2008a). Despite no lower outliers being identified, the neighbourhoods distributed towards the peripheral zones of the city generally experienced lower violent and property crime rates (CTs in the first quartile).

Although there were crime hotspots on either side of Halifax Harbour, the mechanisms underlying the crime distributions may differ. Specifically, previous research indicated that in the northeast of the harbour, violent crime rates tended to be higher in neighbourhoods with higher proportions of populations with lower-education, single-mother families and an overrepresentation of commercial zones, whereas violent crime rates southwest of the harbour tended to be more associated with proportions of people who live alone, and greater proportions of dwellings requiring major repairs (Savoie, 2008a). Property crime rates northeast of the harbour were likely to be higher in neighbourhoods with more commercial zones and higher unemployment rates, while to the southwest of the harbour, property crime rates tended to be higher in neighbourhoods with higher median household incomes and larger proportions of households spending more than 30% of their income on housing (Savoie, 2008a). This is an initial indication of spatial heterogeneity within the boundaries of Halifax.

#### **5.1.4. Spatial Distribution of Crime in the City of Thunder Bay**

The distribution of violent and property crime rates (2001) across 30 neighbourhoods (CTs) within the city of Thunder Bay are shown in Figures 5.7 and 5.8, respectively. A closer examination of the two box maps and box plots indicates that violent and property crime rates displayed similar spatial patterns in Thunder Bay with only two upper outliers identified and no low outliers.

The neighbourhoods with the highest crime rates (CTs corresponding to upper outliers and the first quartile) were generally located along a north-south axis bordering Lake Superior and the Kaministiquia River, with noticeable concentrations in the two downtown areas of the city- the former cities of Fort William and Port Arthur. Similar to the other Canadian cities in the study, the neighbourhoods with low crime rates in Thunder Bay were located towards outlying suburban areas.

Our results are in line with findings from previous research, which indicated that spatial patterns of crime in Thunder Bay were strongly associated with urban development and the resulting differentiation or so-called fragmentation of neighbourhoods (Savoie, 2008a). As the earliest developed areas of Thunder Bay, the core areas of the former cities of Fort William and Port Arthur still serve as the financial, commercial, and entertainment hubs of the region. Thus, high density of commercial and economic activities may in part account for the observed higher rates of crime in these areas. Furthermore, it has been shown that these core neighbourhoods have larger proportions of single people, lone-parent families and Aboriginal population, and include several apartment buildings aimed at housing low income individuals and senior populations (Savoie, 2008a). The overrepresentation of people belonging to at-risk groups (lone-parent families, elderly people living alone and Aboriginals living off reserve) who are likely to have limited access to socioeconomic resources might be another factor contributing to higher crime rates in these areas, since socioeconomic disadvantage may impede these residents to mobilize resources to exert social control and address problems, including crime (Cahill and Mulligan, 2007).

### 5.1.5. Spatial Distribution of Crime in the City of Montreal

Figure 5.9 and 5.10 show the spatial distributions of violent and property crime rates (2001) across 505 neighbourhoods (CTs) in the city (island) of Montreal. It shows that police-reported crimes were not randomly distributed throughout the city, but were concentrated in a limited number of neighbourhoods instead. It was interesting to note that the spatial distributions of crime rates for violent and property offences in Montreal were characterized by an east-west division: in general, the rates of both violent and property incidents tended to be higher in the east of the city, and declined towards the west end of the island. A similar number of upper outliers were identified for violent and property crime rates (n=16 and 17, respectively) and they displayed similar spatial patterns. As observed in other Canadian cities described previously, the neighbourhoods around the urban core in the southeast of the island represent significant violent and property crime hotspots. However, for both types of crime, the highest crime rates were not exclusive to the city center, but they were dispersed among several neighbourhoods throughout the city.

Specifically, although the highest violent crime CTs (upper outliers in Figure 5.9) were largely clustered around the urban core (corresponding to Downtown Montreal, Old Montreal in the Ville-Marie borough<sup>8</sup>), several smaller concentrations also appeared in certain suburban neighbourhoods located in the southeast (Le Sud-Ouest, Verdun boroughs) and the north (Mercier–Hochelaga–Maisonneuve, Montreal-Nord boroughs) of the island. Figure 5.10 shows that the highest property crime rates (upper outlier CTs) exhibited a more compact distribution, which were almost exclusively concentrated in the city center with very few hotspots appearing in the central-east (Rosemont–La-Petite-Patrie borough) and southwest (LaSalle borough) of the

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<sup>8</sup> The detailed Montreal borough map see Savoie et al., 2006

city. Most of these property crime hotspots outside the city center roughly corresponded to the city's different areas of commercial activity (e.g., large shopping malls). Nonetheless, with a few exceptions, the neighbourhoods located in the west section of the island represent markedly lower violent and property crime rates overall.

In short, the spatial distributions of violent and property crime rates in Montreal generally displayed a more dispersed pattern compared to those observed in other Canadian cities that were previously mentioned (e.g., Halifax, Thunder Bay). Several important features regarding the social geography of Montreal may help explain this finding. For example, it has been shown that Montreal has several clusters of low-income neighbourhoods spreading outwards from the city center, in contrast to some Canadian cities (e.g., Vancouver, Winnipeg, Edmonton), where a single dominant cluster of low-income neighbourhoods tends to occupy the downtown core (Heisz and McLeod, 2004). In fact, the revitalisation of the downtown core in Montreal has led to a substantial shift in the location of low-income neighbourhoods in Montreal. In fact, the low-income neighbourhoods in the north of the island, namely in the Hochelaga–Maisonneuve and Montreal-Nord boroughs, contained several hotspots of violent crime (Savoie et al., 2006). Considering the potential spatial correspondence between crime and low-income, the fairly dispersed distribution of low-income neighbourhoods might help explain the observed pattern of crime rates with less of a concentration in Montreal, compared to that of Halifax and Thunder Bay.

#### **5.1.6. Spatial Distribution of Crime in the City of Toronto**

Figures 5.11 and 5.12 show the box maps and corresponding box plots of violent and property crime rates (2006) across 524 neighbourhoods (CTs) in the city of Toronto. The results show that both violent crime and property crime were not uniformly distributed but concentrated in a



limited number of neighbourhoods within the city. However, violent crime and property crime differed with respect to their spatial patterns. As shown in the box map and accompanying box plot of violent crime rates (Figure 5.11), 13 upper outlier CTs with extreme high violent crime rates were identified, which were mainly concentrated in the downtown areas and the northwest areas along Jane Street. No lower outliers for violent crime rates were identified. Similar to Montreal, neighbourhoods with high violent crime rates (CTs in the fourth quartile) were spread out in many areas of the city, which roughly corresponded to areas along the Canadian National railway and to lower income neighbourhoods (Charron, 2009).

Property crime rates showed a slightly different spatial structure (Figure 5.12). The box plot of property crime rates identified 32 upper outliers for property crime rates and no lower outliers were identified. While the majority of the highest property crime rates (upper outliers) were located within the urban core of the city, a more dispersed pattern was observed with several isolated hotspots visible in the north and central-east areas of the city. Many of these correspond to neighbourhoods with large shopping centers and significant commercial activity (Charron, 2009). These results are consistent with previous empirical findings in the crime literature, which indicated that a large amount of mixed or nonresidential landuse, such as land used for businesses or major thoroughfares, may be associated with crime since their high accessibility tends to bring together motivated offenders and potential victims, as well as to create an anonymous setting that might favour crime (Kurtz et al., 1998; Taylor et al., 1995; Wilcox et al., 2004; Stucky and Ottensmann, 2009).

Despite these differences, on the whole, both violent and property crime rates were high in the downtown areas, which extend southwards from Bloor-Danforth Street (upper outlier CTs and CTs in the fourth quartiles), whereas low crime rates tended to be more distributed in the central

and northeast areas of the city (CTs in the first quartile). In line with previous crime studies in Toronto, these low crime areas were either associated with areas where residents earn a high income, or industrial areas and green space of the city (Charron, 2009).

In summary, the interactive use of box maps and box plots in this analysis represents an effective ESDA method for visualizing spatial data and identifying significant outliers, while obtaining a general sense of the statistical distribution of the underlying dataset (Tan and Haining, 2009). The results offer first critical insights into the spatial organization of violent and property crime rates within each city. Regardless of the specific city under study, the results generally supported the notion that urban crime is not distributed evenly or randomly. It is, instead, concentrated in particular neighbourhoods that occupy a relatively small proportion of the city's geographic area. This is an initial indication that spatial effects may be present in the crime data, which provides motivation for further analyses considering spatial autocorrelation.

## **5.2. Spatial Autocorrelation Analysis**

In the previous section, box maps and box plots proved to be useful for describing general spatial patterns of crime rates across neighbourhoods in six Canadian cities, revealing specific neighbourhoods with extreme high or low crime rates. However, they are insufficiently rigorous for identifying significant spatial clustering of crime rates (Messner et al., 1999). That is, the classification of each neighbourhood (CT or DA) in the box maps by quantiles is based only on the level of crime rates in that tract and its relative position in the overall distribution of crime rates for all the neighbourhoods within the city, without considering the spatial association of nearby neighbourhoods in terms of their crime rates. In order to take the spatial arrangement of

crime rates into account, we assessed global and local patterns of spatial autocorrelation by using the Moran's I statistic and its local counterpart (local Moran's I).

As previously noted, spatial autocorrelation is defined as “the coincidence of similarity in value with similarity in location” (Anselin et al., 1988). Spatial autocorrelation can be further classified as either positive or negative. Positive spatial autocorrelation refers to a situation where similar values tend to cluster in space, while negative spatial autocorrelation exists when dissimilar values appear in close geographical or neighbouring locations (Le Gallo and Ertur, 2000). Essentially, spatial autocorrelation analysis allows the assessment of the correlation of a variable in reference to each spatial location of the variable, or how the values at one location relates to values at other (neighbouring) locations (Tan and Haining, 2009). In this study, spatial autocorrelation analysis was used to assess the nature and strength of spatial dependence of neighbourhood (violent and property) crime rates within each city under study. This would further demonstrate whether the observed spatial patterns of crime rates were random or spatially clustered. Furthermore, the results of spatial autocorrelation can potentially help diagnose possible misspecifications in analytical models. That is, the presence of non-spatial independence would suggest that traditional statistical tools (e.g., OLS) for modelling the relationship between crime and contextual characteristics may be inappropriate, as the assumption of independent observations would be violated. It has been shown that ignoring spatial autocorrelation in the model specification may result in false indications of significance, biased parameter estimates, and misleading suggestions of fit (Messner et al., 1999). Therefore, if significant spatial autocorrelation is detected in crime rates, then the model with an adjustment for spatial autocorrelation would be considered to ensure accurate and unbiased results.

### **5.2.1. Global Spatial Autocorrelation**

We began with an assessment of the overall spatial dependence - global autocorrelation - of violent and property crime rates within each city by means of the Moran's I test statistics (Anselin, 1995). The Moran's I provides a global indication of the extent to which the spatial pattern of the entire dataset is compatible with a null hypothesis of spatial randomness, under which the values at one location do not depend on values at other locations (Messner et al., 1999). Rejection of this null hypothesis suggests an overall spatial clustering of the dataset under investigation (Sridharan et al., 2007). Implemented in GeoDa software, significance of the Moran statistic was tested by comparison to a reference distribution generated by random permutations of the observed values (Anselin, 2005). The value of the Moran's I statistic ranges from 1 to -1. A positive value approaching 1 indicates the presence of positive spatial autocorrelation, where areas of similar crime rates (high or low) are clustered together. A negative value approaching -1 indicates the presence of negative spatial autocorrelation, where dissimilar crime rates appear in proximity. A value near zero indicates the absence of spatial autocorrelation (spatial randomness) (Charron, 2009).

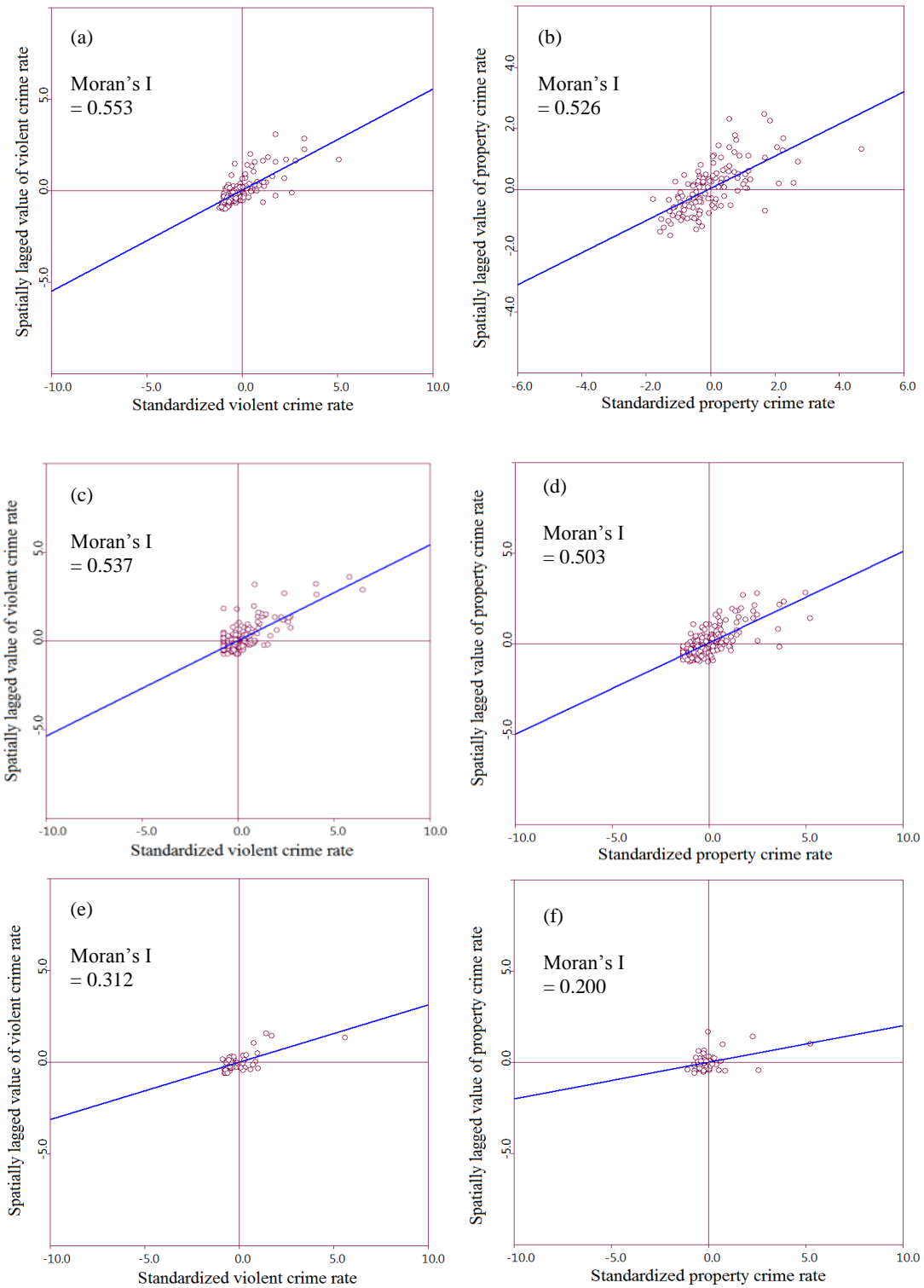
The results for the Moran's I test statistic for global spatial autocorrelation are shown in Table 5.1. The corresponding Moran scatterplots are shown in Figure 5.13, where the spatially lagged value of crime rate (weighted average of the neighbours) is plotted against the standardized original value of crime rate at each CT. The slope of a linear regression line through the scatterplot corresponds to the Moran's I coefficient for global spatial autocorrelation. As shown in Table 5.1, the Moran's I test statistic was positive and significant (based on 999 permutations with a significance level of  $P < 0.01$ ) for both violent and property crime rates in all the six cities under study. This suggests that the null hypothesis of spatial randomness should be rejected,

indicating that positive spatial autocorrelation was present and significant in violent and property crime rates across all the cities under study. The strength of spatial autocorrelation, however, varied among the cities: relatively strong in Edmonton, Saskatoon, Montreal and Toronto, and weaker in Halifax and Thunder Bay. This was probably due in part to the number of neighbourhoods (CTs) available for analysis in the cities of Halifax and Thunder Bay, which are much smaller than those of other cities. Nevertheless, the results provide strong evidence of significant spatial clustering of similar crime rates within each of the cities, such that neighbourhoods tend to have neighbors that also have high rates or, conversely, neighbourhoods with low crime rates cluster together with other low crime rates neighbourhoods.

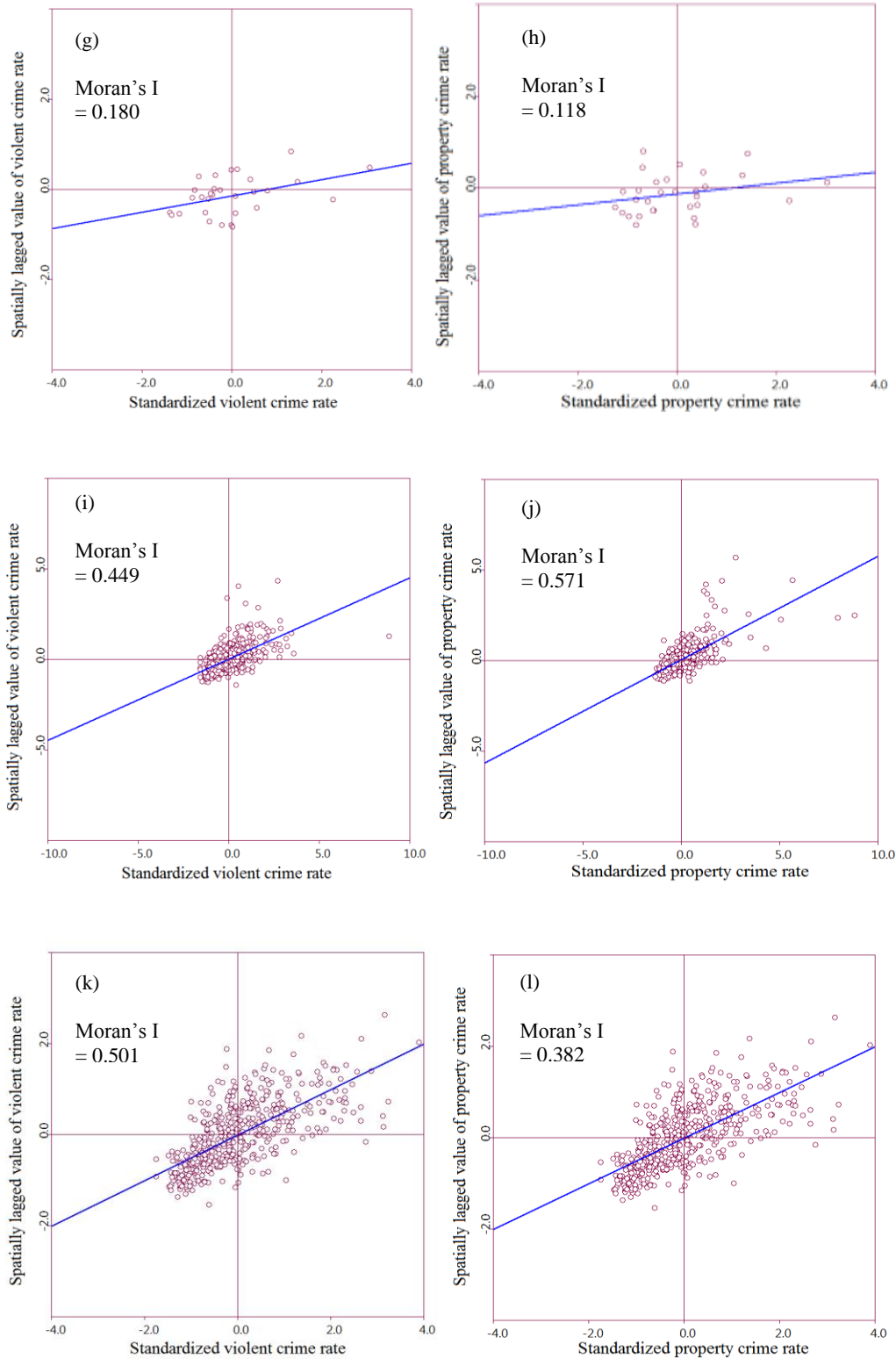
**Table 5.1** - Moran's I statistic for spatial autocorrelation for violent and property crime rate in six Canadian cities

	<b>Edmonton</b>	<b>Saskatoon</b>	<b>Halifax</b>	<b>Thunder Bay</b>	<b>Montreal</b>	<b>Toronto</b>
<b>Violent Crime Rate</b> (per 1,000 combined working and residential population)	0.553	0.537	0.312	0.180	0.449	0.501
<b>Property Crime Rate</b> (per 1,000 combined working and residential population)	0.525	0.503	0.200	0.118	0.571	0.382
<b>Number of neighbourhoods</b>	130	258	51	30	505	524

The test was based on 999 permutations with a significance filter of  $p < 0.01$



**Figure 5.13** - Moran scatterplot for (a) violent crime rates in Edmonton CTs (b) property crime rates in Edmonton CTs (c) violent crime rates in Saskatoon DAs (d) property crime rates in Saskatoon DAs (e) violent crime rates in Halifax CTs (f) property crime rates in Halifax CTs, based on 999 permutations and significance filter of  $P < 0.01$



**Figure 5.13 (continued)** - Moran scatterplot for (g) violent crime rates in Thunder Bay CTs (h) property crime rates in Thunder Bay CTs (i) violent crime rates in Montreal CTs (j) property crime rates in Montreal CTs (k) violent crime rates in Toronto CTs (l) property crime rates in Toronto CTs, based on 999 permutations and significance filter of  $P < 0.01$

### **5.2.2. Local Spatial Autocorrelation**

One limitation of global spatial autocorrelation analysis is that it yields only a single test statistic that pertains to the entire city. Questions remain regarding where spatial clusters of crime rates are located and what type of spatial association is significantly present around a particular location. In order to identify local clusters in the spatial arrangements of crime rates, the so-called local indicators of spatial association (LISA) – implemented through the local Moran's I statistic (Anselin, 1995) – were considered below. The local Moran's I statistic assesses a null hypothesis of spatial randomness by comparing the values (i.e., crime rates) in each neighbourhood (i.e., CT/DA) to values in nearby neighbourhoods (Messner et al., 1999). Rejection of this null hypothesis indicates significant spatial autocorrelation around a specific neighbourhood (i.e., CT/DA). The significance of the local Moran statistic is determined by generating a reference distribution using 999 random permutations (Sridharan et al., 2007).

More importantly, the local Moran statistic allows the decomposition of the pattern of spatial association into four categories, corresponding to four quadrants in the Moran scatterplot (Anselin, 1995; Messner et al., 1999). A neighbourhood's location among these four quadrants implies whether it is classified as a "spatial cluster" or "spatial outlier". Specifically, neighbourhoods in the upper right (high-high) and lower left (low-low) quadrants represent potential spatial clusters, where a neighbourhood with above-average crime rate tends to be surrounded by above-average crime rate neighbours or when a below-average crime rate neighbourhood is surrounded by neighbours with below-average values. Both of these categories imply positive spatial association. By contrast, neighbourhoods in the upper left (low-high) and lower right (high-low) quadrants suggest potential spatial outliers in the form of low crime rates surrounded by high values and vice versa (Sridharan et al., 2007). This is an indication of



negative spatial association. Each of the quadrants corresponds to a different color in the so-called LISA cluster map, which shows the neighbourhoods with significant Local Moran's I statistics and the category of spatial association to which the neighbourhoods belong (Baller et al., 2001). Figures 5.14 to 5.19 display the LISA cluster maps of violent and property crime rates for all six cities. The LISA maps represent a spatial typology that decomposes the citywide pattern of spatial association (observed from the global Moran's I test statistics) into its specific local forms: "high-high" (dark red), "low-low" (dark blue), "low-high" (light blue) and "high-low" (light red) and "not significant" (whited out). It also should be noted that the spatial clusters shown on the LISA Maps only refer to the core of the cluster, and the cluster itself likely includes the neighbors surrounding this location, as defined by the spatial weight matrix (refer to "4.1.2. Spatial Autocorrelation Analysis" for detail). Therefore, the actual cluster usually refers to an area that is larger than that suggested by its core alone (Anselin, 1995).

Beginning with the LISA map (Figure 5.14) for the city of Edmonton, we found evidence of spatial dependency of both property and violent crime rates constrained within the city boundaries. Edmonton appeared to have a, relatively large cluster of high-high violent crime rates (i.e., high-violent crime CTs are surrounded by other high-violent crime CTs) located just north of the downtown area. In contrast, two clusters of low-low violent crime rates were evident with one located in north of the city and a smaller cluster located in the southwestern. Compared to violent crime, property crime rates exhibited a more dispersed pattern with several significant clusters scattered throughout the city. However, similar to violent crime, the largest concentration of high property crime rates was located in the downtown core towards the north. Two smaller clusters of high-high property crime rates were located around the Britannia Youngstown neighbourhood in the east, and around the University of Alberta campus (located

across the North Saskatchewan River from downtown Edmonton). On the other hand, clustering of low property crime rates were found throughout the north, southeast and southwest of the city. Consistent with the patterns previously observed from the corresponding box maps (Figures 5.1 and 5.2), the LISA maps demonstrate a clear north-south division with respect to the spatial patterns of crime rates in Edmonton: the clustering of high crime rates was mostly on the north side of the North Saskatchewan River, while the clustering of low rates were predominantly located in south of the river.

The LISA maps for the city of Saskatoon are shown in Figure 5.15. In general, violent and property crime rates shared similar patterns of local spatial autocorrelation. For both types of crime, the clusters of high-high crime neighbourhoods were primarily located around the Saskatoon urban core, west of the South Saskatchewan River. There was only one small cluster of high-high property crime rates occurring east of the river, located around the commercial areas bordered by the 8th Street. In contrast, two very large clusters of low-low crime neighbourhoods were noticeable in the northeast and southeast peripheral zones of the city. As with Edmonton, the spatial distributions of violent and property crime rates in Saskatoon revealed two distinct spatial regimes: the areas located west of the South Saskatchewan River tended to experience lower crime rates than in the east of it.

The LISA maps shown in Figure 5.16 indicate that both violent and property crime rates in Halifax were characterized by a single cluster of high crime neighbourhood surrounded by other neighbourhoods with high crime rates, which were notably concentrated around the urban core. Low-crime neighbourhoods tended to cluster together as well, however, not exclusively in one area. For both types of crime, two clusters of low crime neighbourhoods surrounded by other with low crime neighbourhoods were present in outlying suburban areas of the city. One was

located in the north end of Mainland Halifax, around Hemlock Ravine Park. Another cluster of low-low crime neighbourhoods was located in the southeast of Dartmouth, corresponding with large green spaces. In addition, property crime rates exhibited another significant cluster of low crime neighbourhoods, located in south Mainland Halifax bordered by the Northwest Arm. Turning to the city of Thunder Bay, the similar profile of spatial clustering appears in the LISA maps of Thunder Bay (Figure 5.17). It shows that both types of crime rates exhibited a single and centralized cluster of high-high crime neighbourhoods in the Fort William downtown area, whereas low-low clusters were evident in peripheral areas of the city.

The LISA maps of violent and property crime rates for Montreal are shown in Figure 5.18. The violent crime rates in Montreal exhibited several significant clusters of hotspots (e.g., high-violent crime CTs surrounded by other high-violent crime CTs) that were not exclusive to the city center. Two of the larger spatial clusters were located around the downtown core and southeast suburban neighbourhoods (Le Sud-Ouest, Verdun boroughs). Two of the smaller clusters were located in the north of the city, near the Mercier–Hochelaga–Maisonneuve and Montreal-Nord boroughs. Low violent crime rates were also clustered together, mainly concentrated in the lower-west side of the island, while another smaller cluster was located in the Anjou borough in the north. In support with the patterns observed in the corresponding box map (previously shown in Figure 5.10), the LISA map (Figure 5.18-b) indicates property crime rates in Montreal had a more concentrated pattern than violent crime rates. Only two high-high clusters were identified, largely limited to the built-up urban core of Montreal: one was located around the downtown core and another in southeast suburbs of the city (Le Sud-Ouest, Verdun boroughs). Similar to violent crime, low property crime neighbourhoods in Montreal appeared to form two significant spatial clusters: the first was a large cluster consisting of the majority of

CTs located in the southwestern section of the island. The second small cluster was located in the northeast peripheral zones approaching the city boundaries.

Similar to Montreal, Toronto appeared to have multiple significant local clusters of high and low crime neighbourhoods (Figure 5.19). Specifically, the first map in Figure 5.19 identified three obvious clusters showing higher violent crime rates. The most centralized cluster was around the downtown east along Bloor-Danforth Street. Two other clusters occurred outside the city center: in the northwest area along a north-south axis centered on Jane Street and near the intersection of Lawrence and Morningside. In contrast, neighbourhoods with low violent crime rates tended to cluster in the north along Yonge Street and peripheral areas located in the northeast and southwest corners of the city. The second map in Figure 5.19 shows property crime rates in Toronto, which resulted in many significant local clusters. The largest concentration of high property crime neighbourhoods was located in the central downtown area, extending southwards from Bloor-Danforth Street. There were also smaller clusters of high property crime neighbourhoods appearing at less centralized locations around the intersections of Jane and Finch, Jane and Highway 401, and Jane and Eglinton. In contrast, low property crime neighbourhoods were significantly clustered in many areas of the city. Similar to the spatial pattern of violent crime, neighbourhoods located in northern areas along Yonge Street and those in outskirt areas towards the northeast appeared to form two large clusters of low property crime rates. Several smaller low-low clusters of property crime rates were also visibly distributed towards the northwestern and western boundaries of the city, as well as along the intersection of Eglinton and Bathur Street.

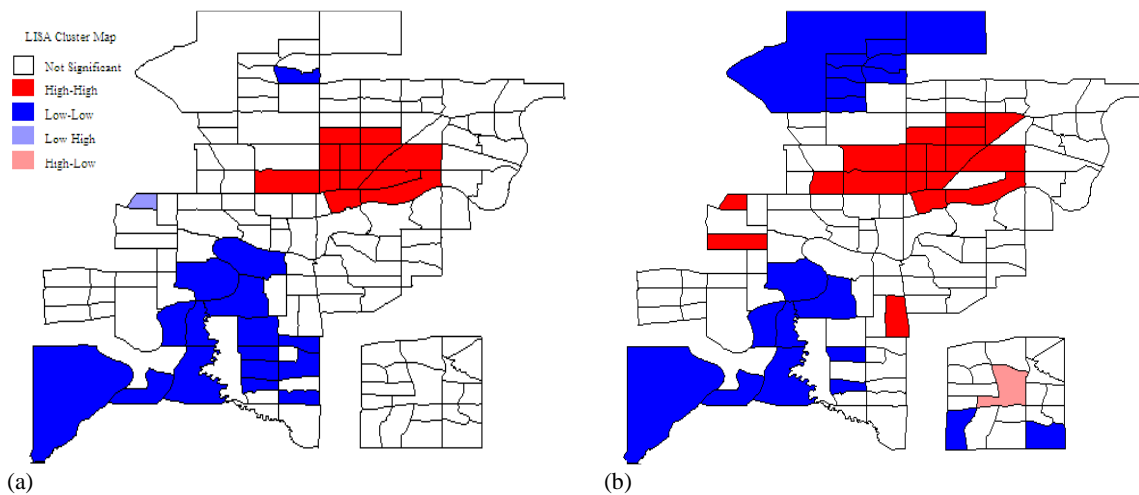


Figure 5.14 – LISA cluster maps of (a) violent crime rates (b) property crime rates for Edmonton CTs, based on 999 permutations and significance filter of  $p < 0.05$

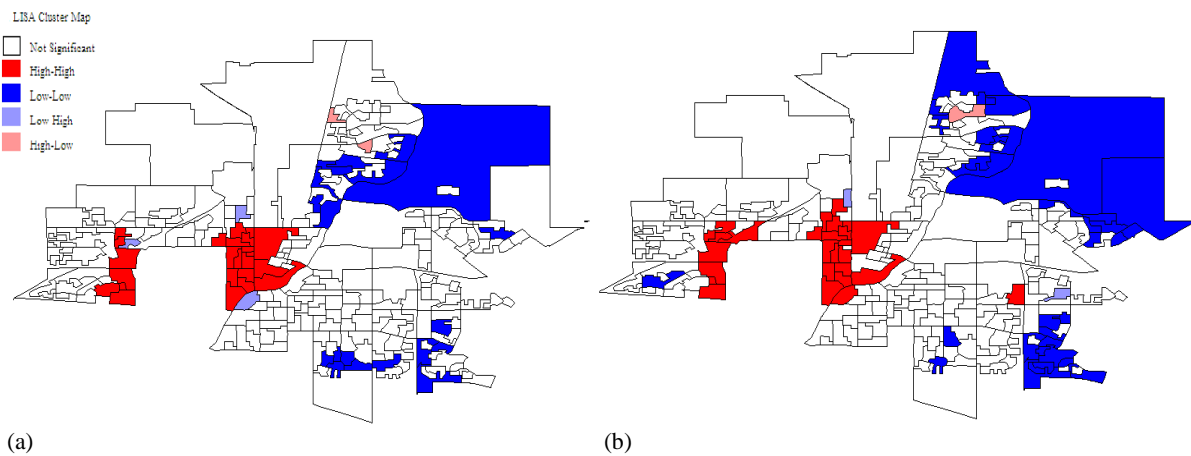


Figure 5.15 – LISA cluster maps of (a) violent crime rates (b) property crime rates for Saskatoon DAs, based on 999 permutations and significance filter of  $p < 0.05$

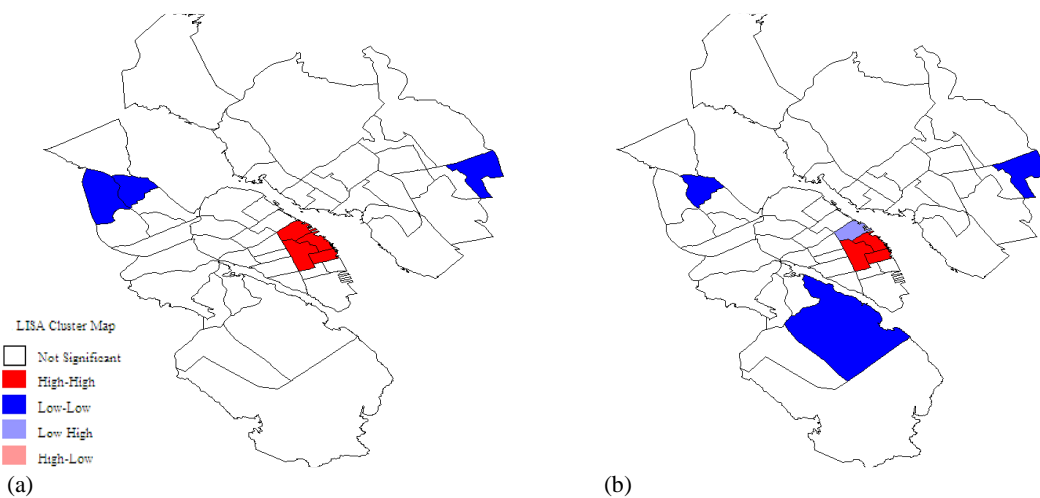


Figure 5.16 – LISA cluster maps of (a) violent crime rates (b) property crime rates for Halifax CTs, based on 999 permutations and significance filter of  $p < 0.05$

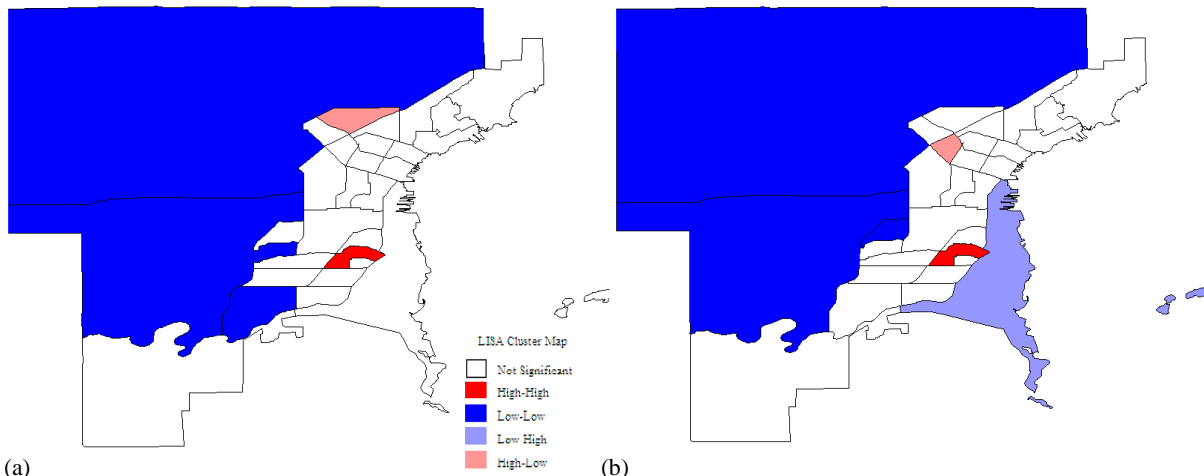


Figure 5.17 – LISA cluster maps of (a) violent crime rates (b) property crime rates for Thunder Bay CTs, based on 999 permutations and significance filter of  $p < 0.05$

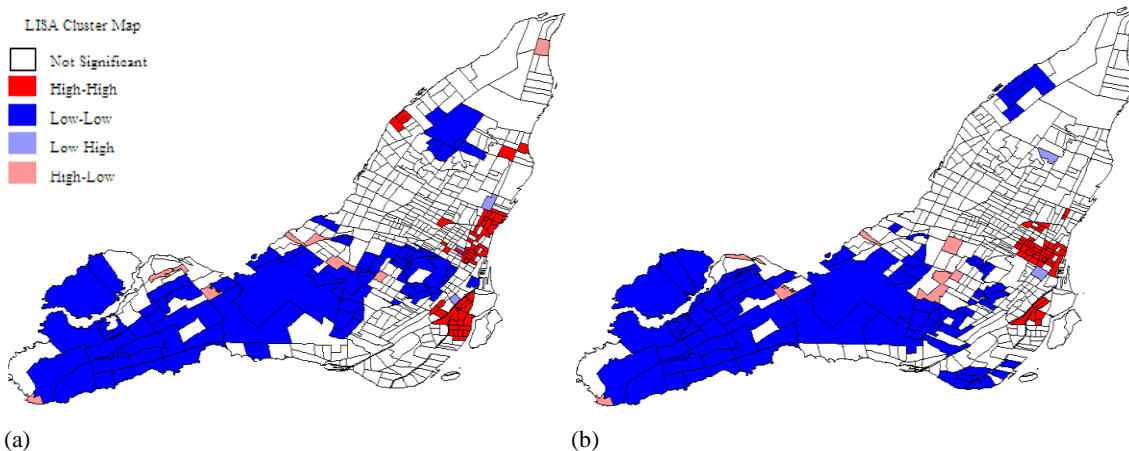


Figure 5.18 – LISA cluster maps of (a) violent crime rates (b) property crime rates for Montreal CTs, based on 999 permutations and significance filter of  $p < 0.05$

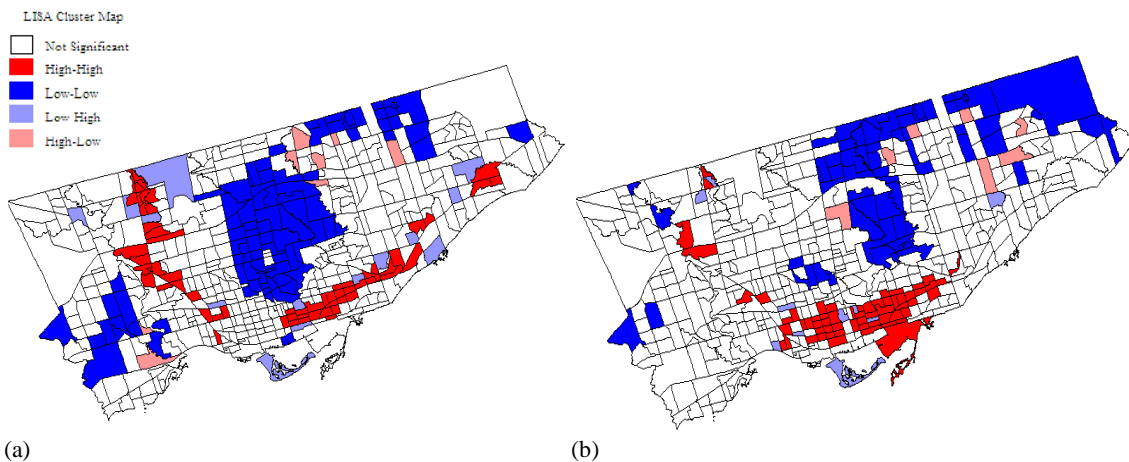


Figure 5.19 – LISA cluster maps of (a) violent crime rates (b) property crime rates for Toronto CTs, based on 999 permutations and significance filter of  $p < 0.05$

### **5.3. Summary**

In summary, our ESDA of neighbourhood crime rates across the six Canadian cities led to several noteworthy findings. First, data visualization by means of box maps and box plots indicated that policed-reported violent and property crimes were not evenly distributed throughout the cities but concentrated in a limited number of neighbourhoods. This is an initial indication that spatial (location) effects in the crime data may be present, which still needs to be verified with tools to formally test for spatial dependence. Therefore, spatial autocorrelation analysis, including Moran's I test statistics and Moran scatterplot, was carried out to test for spatial dependence in the datasets. The results revealed that throughout the six cities under study, neighbourhood-level violent and property crime rates exhibited significant spatial autocorrelation. Therefore, the findings demonstrated the hypothesis that neighbourhoods are interdependent and they have an influence on each other, such that crime rate in a given neighbourhood is likely to be influenced by the characteristics of surrounding neighbourhoods.

Furthermore, the presence of spatial dependence in crime data has important statistical implications. If such spatial effects are not adequately explained by the explanatory variables in the regression models, then the assumptions of independent observations commonly applied in standard regression analysis would be violated (Charron, 2009). This may lead to biased estimation of the model parameters and inaccuracy of the sample variance and significance tests. Therefore, the spatial autocorrelation should be accounted for in the multivariate model of crime rates and neighborhood characteristics to ensure statistically accurate and unbiased results.

Further examination of local patterns of spatial autocorrelation using LISA cluster maps allowed for the identification of local clusters showing positive spatial autocorrelation as well as spatial

outliers. A number of interesting crime “hotspots” (locations of high crime rates clustering together) as well as spatial clusters of low crime rates were found around various neighbourhoods within the cities. As most evidently seen in Halifax and Thunder Bay, high crime rates were significantly clustered in the urban core of these cities, progressing to low crime rates in peripheral suburban areas. This finding is generally consistent with the “concentric zone model” of urban crime derived from the Chicago School’s urban studies (Park and Burgess, 1925; Shaw and McKay, 1942), which suggests that cities tend to expand from the center and to form five concentric zones (Figure 2.1), each with differing characteristics (Park and Burgess, 1925). The transition zone (Zone II) usually experiences more frequent invasion and conflict due to the constant expanding of central business district, which may result in a disruption of social control and higher rates of social problems (e.g., crime) (Roh and Choo, 2008). Moreover, the transition zone is often preferred by low-income people, non-whites, and foreign immigrants since their limited economic ability prevent them from moving out for a better residential environment (Shaw and McKay, 1942). According to social disorganization theory, poverty, ethnic heterogeneity, and population mobility together account for a large amount of high crime rates in the transition zones (Shaw and McKay, 1942). In contrast, the commuter zones in suburbs are typically composed of the middle- or high-class and expensive housing, and tend to experience less social problems, including crime (Park and Burgess, 1925). In support of this “concentric zone model”, our findings suggest that urban crime in Canada can be viewed as a result of complex and continuous urban development.

On the other hand, our ESDA results indicate distinct city differences in the spatial dependence of neighbourhood crime rates. Some cities (e.g., Halifax and Thunder Bay) exhibited a single cluster of high crime neighbourhoods that is exclusive to the urban center. Other cities (e.g.,



Montreal, Toronto) showed multiple clusters of crime hotspots that were scattered throughout the city, rather than constrained to the city center. These findings suggested that the six cities may represent distinct spatial regimes in geographic distributions of crime across neighbourhoods – the spatial geography of the city may interact with neighbourhoods in shaping the spatial organization of crime. This is because social conditions underlying the occurrence of crime are situated in a specific time and place, and thus can be viewed as the result of the urban development process that is potentially city-unique. Therefore, the statistical models of crime and neighbourhood contextual variables based on samples of neighbourhoods encompassing different cities are likely to yield misleading results unless spatial dependency and wider social contexts (i.e., city) are explicitly taken into account.

In conclusion, it should be noted that ESDA is a starting point for analysis and represents the exploratory phase of our research. Although the ESDA approach proved to be particularly effective in detecting interesting spatial patterns and spatial regimes (Baller et al., 2001), it was not able to explain the spatial patterns observed in crime rates. Further identification of causal mechanisms underlying the crime spatial distribution requires formal modeling in a multivariate regression approach. Nonetheless, the patterns of spatial distribution revealed through ESDA suggested that a neighbourhood's spatial context matters when understanding crime rates, thus providing an empirical foundation for the specification of multivariate models in the next stage of analysis.

## Chapter 6 Multilevel Analysis

Results from the exploratory spatial data analysis discussed in Chapter 5 provide an overview of the spatial patterns of crime across neighbourhoods within the six Canadian cities. However, they are not able to explain the spatial patterns observed in crime rates and do not provide any indication of causality. In this chapter, rigorous statistical modelling is applied, wherein the hypothesis regarding the relationship between neighbourhood crime and social context is tested.

Dating back to Shaw and McKay (1942), neighbourhood characteristics have long been linked to crime rates among neighbourhoods. However, with few exceptions (e.g., Kitchen, 2006; Van Wilsem, 2006; Weijters et al., 2009) most studies consider neighbourhoods in one urban area at a time, implicitly assuming that variation across cities is trivial (e.g., Shaw and McKay, 1942; Sampson and Groves, 1989; Elliott et al., 1996; Sampson et al. 1997; Bellair, 1997, 2000). Moreover, these studies have focused exclusively on the internal properties of neighbourhoods while ignoring the wider social environment surrounding a given neighbourhood which may potentially have an impact on crime rates (e.g., city characteristics). As a result, questions remain regarding whether such neighbourhood-level models can be generalized across cities and whether social contexts beyond neighbourhoods can have independent effects on neighbourhood crime rates.

This chapter expands previous research on neighbourhood crime by considering not only the local neighborhood but also the wider spatial context within which the neighborhood is embedded. Using data from the 2001 Uniform Crime Reporting Survey (UCR2) and the 2001 census for six Canadian cities, the analysis presented in this chapter explores the relationships of neighbourhood rates of violent and property crime with both neighbourhood- and city-level

characteristics with adjustments for spatial dependence. Methodologically, this is accomplished by using a combination of hierarchical linear models and spatial regression models (please refer to “4.2 Multilevel Analysis” for details).

Specifically, the objectives of this chapter are four-fold. First, it explores whether neighbourhood-level crime rates vary significantly across the cities. In this way, it examines the proportion of total variance in neighbourhood crime rates that is attributed to differences between cities versus differences between neighbourhoods. Second, the chapter examines the extent to which neighbourhood rates of violent and property crime can be explained by the socioeconomic, demographic and dwelling features of neighbourhoods, after controlling for city random effects. This procedure allows an estimation of the pooled within-city relationship between neighbourhood crime rates and the neighbourhood contextual variables by isolating the between-city differences. Third, by incorporating spatial econometric techniques (i.e., spatial regression models) into the multilevel models, the chapter assesses the robustness of the neighbourhood predictors of crime rates with rigorous controls for spatial dependence. This also indicates whether crime rates in a given neighbourhood are related to characteristics of adjacent neighbourhoods. Finally, the chapter assesses whether social contexts as large as cities have an impact of their own on neighbourhood crime rates. This is done by relating city-level characteristics to neighbourhood rates of crime, while adjusting for compositional (neighbourhood) differences.

In order to address the aforementioned objectives, four separate hierarchical linear (random-intercept) models were estimated for each type of crime. First, a fully unconditional model without any predictor variable was estimated to determine the amount of variance in crime rates at the city level as well as at the neighbourhood level. Second, neighbourhood-level variables

were added to the models to examine whether neighbourhood crime rates can be attributed to the socioeconomic, demographic and dwelling features of neighbourhoods, controlling for the city random effects. Next, focusing on spatial effects, the subsequent model added a spatial lag term (weighted average of crime rate in adjacent neighbourhoods) to see if it has moderated the impacts of neighbourhood contextual variables in shaping neighbourhood crime rates. Finally, a fully-random intercept model including both city- and neighbourhood-level variables was estimated to examine the influences of city characteristics over and above neighbourhood-level factors and to determine the degree to which both neighbourhood- and city-level characteristics account for the variation in neighbourhood crime rates across cities. The equations for each of these models are displayed in Appendix A.3. The results of these analyses are summarized in the following section.

## **6.1. Model 1 - Assessing Baseline Variance**

We began our multilevel analysis by assessing the degree to which the dependent variables (i.e., violent or property crime rates) vary across the cities. For this purpose, we estimated a one-way random-effect analysis of variance (ANOVA) model (Raudenbush and Bryk, 2002), which is an unconditional model that contains no explanatory variable but decomposes the variance of the dependent variable into within- and between-group components (Raudenbush and Bryk, 2002).

Although this null model cannot test any hypothesis regarding the relationships of crime rates with either neighbourhood-level or city-level characteristics, it does serve as a baseline for comparison with subsequent, more elaborate models. That is, it indicates how much of the total variance in the dependent variables (i.e., crime rates) is within cities (level-1) versus between cities (level-2), from which the intra-class correlation coefficients (ICC) described above can be

estimated. Through this model, we are able to determine whether to proceed with more complex models and to identify the level at which introducing explanatory variables are more likely to account for the variance.

Table 6.1 displays the results from the null models presenting the intercept and variance components for violent and property crime rates. The intercept<sup>9</sup> corresponds to the overall mean of each dependent variable, in this case, the average violent or property crime rates per neighbourhood across all the cities. It shows that violent crime rate was relatively low in an average urban neighbourhood across all the cities in this study, corresponding to an average of about 12 incidents per 1,000 residents. Neighbourhood property crime rates were higher, corresponding to a mean rate of 47 incidents per 1,000 residents for all the cities.

The “random effects” panel of the table indicates significant variance in both types of crime rates across the cities. Specifically, the city variance in neighbourhood violent crime rates was significantly greater than 0 ( $\tau = 43.314$ ,  $p < 0.001$ ), which accounted for about 34% of the total variance in violent crime rates (ICI = 0.34). Similar findings are reported for property crime rates. Roughly 45% of the total variance in property crime rates could be attributed to the differences between city contexts (ICI = 0.45). It appears that most of the variance in the dependent variables (i.e., neighbourhood violent and property crime rates) was attributable to within city differences (level-1) rather than between cities (level-2). Nevertheless, these preliminary results suggest that cities do differ significantly in average neighbourhood crime rates and therefore, the city context is important to consider for better understanding neighbourhood crime rates in Canadian urban settings.

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<sup>9</sup> Ideally, a confidence interval of the intercepts across cities would be estimated to better assess the between-city variance (For a detailed discussion see Raudenbush and Bryk, 2002, p. 291-335). However, it is less informative in the case of small sample sizes at level two (N=6).

**Table 6.1** - One-way random-effect ANOVA models for violent and property crime rates

	<b>Violent crime rates</b>		<b>Property crime rates</b>	
<b>Fixed effects</b>	Coefficient	S.E.	Coefficient	S.E.
Intercept (City mean neighbourhood crime rates)	11.539**	2.715	46.524**	10.656
<b>Random effects</b>	Variance	Chi-square	Variance	Chi-square
City-level (level-2)	43.314***	279.935	671.291***	700.534
Neighbourhood-level (level-1)	82.840		821.429	
<b>Intra-class correlation coefficients (ICC)</b>	0.343		0.450	
<b>Deviation</b>	10,751.433		14,144.358	

\*\*\*p<0.001, \*\*p<0.01

## 6.2. Model 2 - Controlling for Neighbourhood-level Characteristics

It is reasonable to assume that at least part of the observed variation in crime rates across neighbourhoods can be explained by the local conditions of neighbourhoods, such as their socioeconomic and demographic characteristics. Therefore, we have expanded the unconditional models (Model 1) with several neighbourhood-level variables to investigate possible neighbourhood contextual effects. The neighbourhood-level variables were based on 2001 Statistics Canada Census measures of some aspects of social, economic and demographic characteristics in the population (see “3.3.3 Variables and Measures” for the detailed explanation of these variables).

More specifically, the goal in this model was to answer two research questions. First, which of those neighbourhood characteristics investigated were significantly related to crime rates while controlling for city random effects? Second, did adding the neighbourhood-level variables account for some of the unexplained variability of crime rates observed in the null model? In order to address these questions, we developed a one-way random-effect ANCOVA model (Raudenbush and Bryk, 2002) which included a full set of the seventeen neighbourhood-level variables described above (Table 4.1) as the level-1 predictors while no city-level variables were

specified at level-2. All these neighbourhood variables were centered by their group (city) mean to isolate differences between cities and yield an estimate of the pooled within-city slope<sup>10</sup>. Only level-1 intercepts were allowed to vary and all the neighbourhood-level slopes were fixed across the cities.

This model provided a critical insight into the relative effects of each neighbourhood characteristic and thus identified the specific neighbourhood-level variables that were most strongly related to neighbourhood crime rates after controlling for city random-effects. Initial estimation of this full model suggested that some of the neighbourhood-level variables were not significantly associated with violent or property crime rates. Therefore, proceeding by a backward elimination process<sup>11</sup>, we estimated a reduced model with results reported in Table 6.2.

**Table 6.2** - One-way random-effect ANCOVA models for violent and property crime rates

<b>Fixed Effects</b>	<b>Violent Crime Rate</b>		<b>Property Crime Rate</b>	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept (city mean neighbourhood crime rates)	11.557**	2.727	46.538**	10.670
<b>Neighbourhood-level Variables<sup>a</sup></b>				
Index of concentration at the extremes (ICE)	-3.291* (-0.089)	1.538	-16.558** (-0.130)	3.882
Percentage of Aboriginal population	0.657** (0.359)	0.051	1.793** (0.284)	0.179
Percentage of dwellings built before 1961	0.021** (0.069)	0.007	--	--
Percentage of dwellings that require major repairs	--	--	0.519** (0.077)	0.151
Percentage of lone-parent	--	--	-0.206*	0.092

<sup>10</sup> As discussed in Raudenbush and Bryk (2002), group-mean centering is most appropriate in situations where the primary substantive interest is the effects of level-1 predictors. This follows the fact that group-mean centering removes all between-group variation from the predictor and thus produces an unbiased estimated of the within-group slope (level 1 relationship between the predictor and outcome variable) (Enders and Tofghi, 2007).

<sup>11</sup> The backward approach began with a full set of the 17 neighbourhood-level explanatory variables, with variables subsequently being eliminated that were not significant. This procedure is performed interactively until all variables in the model are tested significant ( $p < 0.05$ ). The order for deletion is determined by using the p-value as the criterion (i.e., eliminating the most insignificant variable in each step).

families			(-0.054)	
Percentage of owner-occupied household	-0.045** (-0.124)	0.014	-0.109* (-0.086)	0.045
Percentage of people who are single	--	--	0.248** (0.089)	0.074
Percentage of population aged 65 years and over	-0.113** (-0.092)	0.028	--	--
Percentage of recent immigrants	-0.150** (-0.167)	0.029	-0.648** (-0.210)	0.095
Percentage of residents without high school diploma	0.146** (0.181)	0.025	--	--
Residential stability	-0.058* (-0.077)	0.024	-0.217** (-0.083)	0.078
Unemployment rate	0.317** (0.135)	0.062	0.684** (0.085)	0.213
<b>Random Effects (Residual Variance)</b>	Variance Component	Variance Explained (R <sup>2</sup> )	Variance Component	Variance Explained (R <sup>2</sup> )
Between cities (level-2)	43.984**	-1.546 <sup>a</sup>	675.273**	-0.593 <sup>b</sup>
Within cities (level-1)	53.749	35.116	625.749	23.822
<b>Deviation</b>	10,147.869			13,750.464

\*\*p<0.01, \*p<0.05

a. All neighbourhood-level predictors are group mean centered. Unstandardized coefficients are reported with standardized coefficients in parentheses.

b. With group-mean centering, the level-2 variance in intercept is equal to the variance in the unadjusted mean of the outcome variable. Therefore, there would be little or no change in the estimate of the level-2 variance in intercept compared to that of the null model. Thus, the variance explained at level-2 should be close to zero. However, negative R<sup>2</sup> at level-2 is possible in multilevel modeling (more discussion see Kreft and De Leeuw, 1998, p.118-119), since the inclusion of variables with a small amount of between-group variation (i.e., group-means) may increase the between-group residual variance.

The results for violent crime rates are reported in the first two columns of Table 6.2. It shows that on average, a set of nine neighbourhood-level variables were significantly associated with neighbourhood violent crime rates within cities ( $p < 0.05$ ). The residual variance at level-1 (within-city variance) for this model was reduced to 53.749 compared to a value of 82.840 for the null model (see Table 6.1). This means that about 35% of the observed within-city variance in neighbourhood violent crime rates was accounted by this set of neighbourhood-level variables, although a large amount of this variance remains to be explained. The results suggest that other



features of neighbourhoods beyond the socioeconomic and demographic characteristics (e.g., the type of land-use, collective efficacy, institutional resources, community engagement etc.) possibly responsible for this variation may need to be explored. Furthermore, a comparison of the deviation statistics for the null model and the current random-effects ANCOVA model indicates that incorporating explanatory variables at the neighbourhood level have led to a significant improvement of the model fit (Deviation = 10,147.869 compared to 10,751.433).

The main effects of these neighbourhood-level variables are displayed in the “fixed effects” panel of Table 6.2. As each of these neighbourhood-level variables are centred around their group means, the regression coefficient provides an unbiased estimate of the pooled within-city slope, on average, the expected change in neighbourhood crime rates corresponds to one unit increase in a neighbourhood-level variable across all the cities. In order to compare the relative effects of the neighbourhood characteristics, the corresponding standardized coefficients are also indicated in parentheses, which refers to the expected variation in standard deviation units of crime rates corresponding to one standard deviation unit increase of a neighbourhood-level variable when all other variables are held constant.

An examination of these standardized coefficients reveals that among all these variables included, the proportion of Aboriginal population made the largest contribution to the explanation of violent crime rates at the neighbourhood level. This finding is consistent with results obtained by previous studies that the Aboriginal population in Canada is over-represented among victims and offenders (Richards 2001; La Prairie 2002; Brzozowski et al., 2006). According to the 2004 General Social Survey (GSS) on victimization, the rates of Aboriginal people experiencing violent victimization were reported as three times higher than that of non-Aboriginal people (Gannon and Mihorean, 2005). In support of social disorganization theory, two measures of

socioeconomic disadvantage – unemployment rate and low educational attainment (the proportion of population aged 20 and over without a high school degree) appear to be leading factors that contribute to neighbourhood violent crime rates across the cities. Two guardianship measures, residential stability and percentage of owner-occupied household, were generally negatively related to neighbourhood violent crime rates. This might be due to the enhancement of people's sense of attachment to their places of residence and neighbourhoods, which may encourage more investment in their neighbourhoods and may subsequently lead to more development of social control and mobilization of resources for addressing problems of crime (Cahill and Mulligan, 2007). Furthermore, after accounting for other neighbourhood-level variables, neighbourhoods with high concentrations of recent immigrants tend to exhibit lower rates of violence. This result is in line with previous studies of neighbourhood crime in Canada, which have largely found an insignificant or negative link between immigrant status and crime (e.g., Charron, 2008, 2009). Violent crime rates were also lower in neighbourhoods where there were higher proportions of elderly population (population aged 65 and over), most of whom are more likely to be home at any given time of day. This may act as a deterrent of crime, since elderly residents may informally watch over neighbourhoods (Charron, 2009).

In addition, the Index of concentration at the extremes (ICE), which captures the degree of concentrated affluence relative to the concentration of poverty in a neighbourhood (Massey, 2001), was negatively related to violent crime rates. This indicates that neighbourhoods with larger concentrations of affluent families (relative to poor families) tend to experience lower levels of violent crime. This provides support for the theory that affluent neighbourhoods protect against violence based on the ease of access to and mobilization of various resources (Morenoff et al., 2001). Finally, the proportion of aging dwellings (built before 1961) in a neighbourhood

exerted a smaller yet significantly positive effect on violent crime rates, supporting this variable as a measure of physical environmental degradation that may promote crime. This is in accordance with the broken window theory, which suggests that the deterioration of physical environments is likely to make the impression of not caring and ambivalence, which may lead to further degradation of social cohesion within the community that would otherwise favor social control of crime (Brown et al., 2004; Charron, 2008).

Results of the property crime model (last two columns of Table 6.2) indicate that across the cities studied, nine of seventeen neighbourhood characteristics were significantly related to neighbourhood property crime rate, many of which were just the factors that significantly impacted neighbourhood violent crime rate. Similar to that observed in violent crime, the proportion of Aboriginal people has the greatest explanatory power for property crime rates at the neighbourhood level across the cities (recorded as the highest standardized coefficient among all the explanatory variables included). When all other factors were held constant, property crime rates were likely to be lower in affluent neighbourhoods and those with a higher proportion of recent immigrants. Unemployment rate was a significant factor contributing to higher property crime rates in a neighbourhood, as well to violent crime. Residential stability and percentage of owner-occupied households also had protective influence on property crime rates in neighbourhoods. As another indicator of the degradation of a neighbourhood's physical environment (one is the proportion of dwellings built before 1961), the proportion of dwellings requiring major repairs was positively associated with property crime rates.

Despite these similarities, property crime rates showed a significant association with family structure, measured by the proportion of single population and proportion of lone-parent families in a neighbourhood. On average, the higher proportion of single population in a neighbourhood,

the higher rates of property crime rates given all other variables being equal. This finding supports the hypothesis drawn from routine activity theory, which suggests that the lifestyles of single persons (e.g., going to bars and nightclubs) are likely to place them at higher risk of being either offenders or victims (Hirschi and Gottfredson, 1983; Land et al., 1990). The parameter estimate for the proportion of lone-parent families was negative, which is opposite to what is expected by social disorganization theory on the expectation that family disruption is a leading predictor of juvenile delinquency and crime (Sampson and Groves, 1989). A further exploration of the effects of lone-parent families suggests that their significant effects dissipate once the variable – the proportion of single population – was dropped from the model. This is possibly due to the problem of multicollinearity – the proportion of single population is highly correlated with the proportion of lone-parent families ( $r = 0.426$ ,  $P < 0.05$ ), as shown in the correlation matrix provided in Appendix A.2. This correlation may distort some regression coefficient estimates and make it difficult to disentangle the effects of single population on crime rates from those of lone-parent families.

The variance components for the property crime model are reported in the “random effects” panel of Table 6.2. When taken together, the set of neighbourhood-variables has accounted for approximately 24% of the total variance between neighbourhoods in property crime rates (the between variance has reduced from 821.429 to 675.273). Again, the deviation test shows that the fit of this model was far better than the null model without any explanatory variable.

In summary, the results from the random-effects ANCOVA models indicate that some of the neighbourhood socioeconomic, demographic and dwelling characteristics explained part of the variance in crime rates across neighbourhoods; however, a considerable amount of this variance was left unexplained (about 65% for violent crime, 76% for property crime), suggesting that the

neighbourhood differences in crime rates were not totally captured by the contextual characteristics of those neighbourhood themselves. Some important crime-related factors that are missing from this model might improve the results. Specifically, other features of neighbourhoods beyond the socioeconomic and demographic characteristics might explain the observed variance in neighbourhood crime rates. Such factors may include, for example, collective efficacy<sup>12</sup>, institutional resources, community engagement, and the type of land-use (Savoie, 2008b). Furthermore, it has been shown that individuals' rates of offending (or risk of victimization) are partially determined by their personal characteristics (e.g., age, education, income, race etc.) (Cohen and Felson, 1979; Colvin, 2000; Kubrin and Weitzer, 2003b). Thus, the distribution of people with certain characteristics within a neighbourhood may produce a compositional effect on aggregated crime outcomes. Therefore, future research examining neighbourhood explanation of neighbourhood crime rates would benefit from the addition of individual-level variables that measure personal characteristics of residents.

### **6.3. Model 3 - Controlling for Neighbourhood Interdependence**

The analysis so far has been restricted to exploring contextual effects in terms of the internal characteristics of neighbourhoods, while ignoring the potential influence that the wider social environment surrounding a given neighbourhood may have on its crime rates. As previously noted, neighbourhoods whose boundaries are imposed by census geography (i.e., census tract) are seldom spatially independent and thus observations at proximal neighbourhoods are unlikely to be independent of one another. With reference to the spatial distribution of crime, levels of crime in one neighbourhood are likely to be influenced by levels of crime in nearby

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<sup>12</sup> "Social cohesion among neighbours combined with their willingness to intervene on behalf of the common good." (Sampson et al., 1997)

neighbourhoods, as well as proximate contextual mechanisms (i.e., poverty, residential mobility) that may crosscut geographic areas (Baller et al., 2001). Our previous spatial autocorrelation analysis (more detail see Chapter 5) indicates that spatial dependence was present and significant in crime rates at the neighbourhood level in most of the cities. If not being accounted for, the spatial dependence may cause the neighbourhood-level (level-1) residuals to be not randomly distributed, thus violating the assumption of the hierarchical linear models that level-1 residuals are normally and independently distributed. Therefore, omitting such spatial effects in the hierarchical models of crime rates and contextual characteristics would misrepresent spatial relationships among the variables involved. Given theoretical recognition and empirical evidence of inter-neighbourhood dependence, as well as concerns about potentially misspecified models that do not account for spatial effects, a hierarchical linear model that incorporates a specification of spatial dependence is considered in subsequent analyses.

Specifically, the spatial dependence of neighbourhood crime rates was accounted for by using spatial lag regression models<sup>13</sup>(Anselin, 1988), in which spatial dependence is introduced as an additional explanatory variable, the so-called “spatial lag term” or weighted average values for the dependent variable in neighbouring areas (i.e., contiguous first-order neighbours) (Baller et al., 2001). The formal equation is expressed as:

$$y = \rho W y + \beta X + \epsilon \tag{Eq.6.1}$$

Where  $\rho$  is the spatial autoregressive coefficient, and  $W$  is a weights matrix that expresses a form of spatial association among each pair of neighbourhoods. In this case, it is expressed as

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<sup>13</sup> Spatial dependence can also be treated as a nuisance in a spatial error model (Anselin, 1988). The spatial lag model was chosen because it is more appropriate in the analysis presented here where spatial dependence is substantive interest rather than as a nuisance.

first-order rook contiguity, which defines neighbours as those neighbourhoods sharing a common border, i.e.,  $W_{ij} = 1$  if and only if neighbourhoods  $i$  and  $j$  have a border in common, otherwise  $W_{ij} = 0$ . This weight matrix implies that the crime rates in a focal neighbourhood is influenced by the characteristics of nearby neighbourhoods and that each of these influences is equally strong (as the relevant  $W_{ij}$  are all equal to 1) (Bernasco and Elffers, 2010). Thus, for a given neighbourhood  $i$ ,  $Wy_i$ , is the weighted average of values of  $y$  in  $i$ 's first-order neighbours,  $\sum_j W_{ij} y_j$ .  $X$  is a matrix of exogenous explanatory variables with an associated vector of regression coefficients  $\beta$ ; and  $\epsilon$  is a vector of normally distributed, random error terms with means 0 and constant variances (Morenoff *et al.*, 2001).

Essentially, the spatial lag regression model is compatible with the notion of “diffusion processes”, since it relates the value of  $y$  at one location to values of  $y$  in contiguous neighbouring locations through  $\rho$  (Morenoff, 2003). In other words, it implies that crime events in one neighbourhood diffuse outward and increase the likelihood of crimes in surrounding neighbourhoods (Baller *et al.*, 2001). As cited in the literature, interpersonal crime such as assault and homicide are based on social interactions that may cross neighbourhood boundaries, and as a result may be subject to diffusion processes – acts of violence that occur in one neighbourhood may generate a sequence of events that eventually lead to further violence in an adjacent neighbourhood<sup>14</sup> (Morenoff *et al.*, 2001). In some situations, however, diffusion is not a theoretical possibility (e.g., perhaps not all types of crime are subject to diffusion processes). In this case, the interpretation of the spatial lag regression model will rest on the operation of spatial

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<sup>14</sup> It should be recognized that the concept of diffusion is a sequential process that occurs over time (i.e., events in a given place at a given time influence events in another place at a later time) (Baller *et al.*, 2001) and cannot be completely captured by the spatial lag model that based on cross-sectional data (e.g., crime rates that are spatially interrelated across neighbourhoods while being simultaneously determined) (Morenoff *et al.*, 2001). Further inquiry into the nature of diffusion mechanisms is warranted, whereas it is beyond the scope of the present study.

externalities - the measured and unmeasured predictor variables (i.e., error term) in spatially proximate neighbourhoods. Extending the logic of equation (6.1) reveals that if the value of  $y$  in neighbourhood  $i$  is a function of the values of  $X$  and  $\epsilon$  in neighbourhood  $i$  and values of  $y$  in  $i$ 's first-order neighbours, then it follows that values of  $y$  in the first-order neighbours are, in turn, functions of  $X$  and  $\epsilon$  in  $i$ 's first-order neighbours and of  $y$  in the second-order neighbours, and so on (Morenoff, 2003). To be clear, we can rewrite equation (6.1) in its reduced form:

$$\begin{aligned}
 y &= \beta X + \rho W X \beta + \rho^2 W^2 X \beta + \dots + \rho^m W^m X \beta + \epsilon + \rho W \epsilon + \rho^2 W^2 \epsilon + \dots + \rho^m W^m \epsilon \\
 &= (1 - \rho W)^{-1} X \beta + (1 - \rho W)^{-1} \epsilon
 \end{aligned}
 \tag{Eq.6.2}$$

This process, known as a “spatial multiplier” (Anselin, 2003b), continues to expand until it reaches the border of the city (Morenoff et al., 2001). This equation clearly illustrates that the observed  $X$  variables or the error term  $\epsilon$  (unobserved predictors) at a given neighbourhood influence not only the value of  $y$  at that neighbourhood but also all other neighbourhoods within the city. In summary, the spatial lag regression model defined in equation (8) captures spatial effects that operate through any of the following mechanisms: (1) spatial exposure to the observed independent variables (e.g., the measured neighbourhood characteristics), (2) spatial exposure to unmeasured factors that were left out of the model but associated with crime rates (i.e., the error term), or (3) endogenous diffusion or feedback effects in crime rates (i.e., effects of crime rates of adjacent neighbourhoods upon each other) (Morenoff, 2003).

The simultaneous estimation of spatial lag regression models within HLM is currently not available. Nonetheless, we effectively joined a multilevel and spatial lag model by employing a two-step procedure. First, the spatially lagged term (i.e.,  $Wy$ ), which amounts to the weighted average of crime rate in nearby neighbourhoods, was calculated for each of the neighbourhoods



included by using GeoDa software. Then, the spatially lagged variables were imported into HLM along with other neighbourhood-level variables (as specified in Table 6.2) as the level-1 predictors for multilevel modelling of the neighbourhood crime rates<sup>15</sup>.

Table 6.3 displays the maximum likelihood results for the spatial regression model estimated for violent and property crime rates. For both types of crime, further extending the model with the spatial lagged terms at neighbourhood level has led to a significant improvement in the overall fit of the model (i.e., Deviation decreased from 10147.869 to 9735.978 for the violent crime model, from 13750.464 to 13394.600 for the property crime model).

The spatial lagged term was positive and statistically significant in both the violent and property crime models. This provides evidence that there are significant spatial dependence effects present in both types of neighbourhood crime rates, even the internal neighbourhood characteristics have been accounted for. An examination of standardized coefficients further verifies the presence of such spatial dependence effects - the influences of nearby neighbourhoods on one another, as the strongest predictors of neighbourhood crime rates for both violent and property offences (recorded as the highest standardized coefficient among all the explanatory variables that were included).

Furthermore, the introduction of the spatial lagged term has dramatically influenced the estimated effects of socioeconomic, demographic and dwelling characteristics of neighbourhoods on crime rates. More specifically, when the spatial lagged term was controlled in the property crime model, only the effects of Aboriginal population, ICE, dwellings requiring major repair and recent immigrants remained significant ( $P < 0.05$ ), although reduced substantially in

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<sup>15</sup> Since the level-1 equation of this hierarchical model has an endogenous variable on the right-hand side,  $W_y$ , it should be estimated using either a maximum likelihood (ML) or two-stage least squares (2SLS) approach (Anselin 1988). The former is currently applied in HLM.

magnitude. Similarly, the control for spatial dependence in the violent crime model eliminated the significance of ICE, dwellings built before 1961, recent immigrants and residential stability in mitigating violence ( $P > 0.05$ ) and significantly reduced the magnitude of other predictor coefficients from Model 2 (Table 6.2), which remained significant. Since all the neighbourhood-level predictors showed a weaker association with crime rates after the spatial lagged variables were introduced, there is reason to believe that the ecological impact of internal neighbourhood characteristics may be partially attributed to the spatial effects arising from the interdependence among neighbourhoods.

**Table 6.3** - Spatial hierarchical linear models for violent and property crime rates

<b>Fixed Effects</b>	<b>Violent Crime Rate</b>		<b>Property Crime Rate</b>	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept (city mean neighbourhood crime rates)	11.566**	2.732	46.549**	10.679
<b>Neighbourhood-level Variables<sup>a</sup></b>				
Index of concentration at the extremes (ICE)	-0.573 (-0.015)	1.339	-7.990* (-0.063)	3.455
Percentage of Aboriginal population	0.301** (0.164)	0.047	0.815** (0.129)	0.165
Percentage of dwellings built before 1961	0.007 (0.022)	0.006	--	--
Percentage of dwellings that require major repairs	--	--	0.339* (0.050)	0.134
Percentage of lone-parent families	--	--	-0.093 (-0.024)	0.081
Percentage of owned-occupied household	-0.040** (-0.109)	0.012	-0.049 (-0.039)	0.040
Percentage of people who are single	--	--	0.043 (0.016)	0.066
Percentage of population aged 65 years and over	-0.084** (-0.069)	0.024	--	--
Percentage of recent immigrants	-0.034 (-0.038)	0.025	-0.266** (-0.086)	0.086
Percentage of residents without high school diploma	0.059** (0.073)	0.022	--	--

Residential stability	0.003 (0.004)	0.021	-0.111 (-0.043)	0.069
Spatial lag term	0.780** (0.545)	0.035	0.717** (0.559)	0.035
Unemployment rate	0.226** (0.097)	0.054	0.312 (0.039)	0.189
<b>Random Effects (Residual Variance)</b>	Variance Component	Variance Explained ( $R^2$ )	Variance Component	Variance Explained ( $R^2$ )
Between cities (level-2)	44.283**	-2.236	678.078**	-1.011
Within cities (level-1)	40.411	51.218	488.387	40.544
Deviation	9,735.978		13,394.600	

\*\*p<0.01, \*p<0.05

a. All neighbourhood-level predictors are group mean centered. Unstandardized coefficients are reported with standardized coefficients in parentheses.

A further decomposition of the spatial effects hinges on the interpretation of the spatial autoregressive coefficient  $\rho$ . Primarily, the  $\rho$  coefficient for the spatial lag term (i.e.,  $W_y$ ) captures the effects of the dependent variables in nearby neighbourhoods to the dependent variable in the focal neighbourhood. The findings support the claim that independent of internal social contextual characteristics, crime rates in a neighbourhood tend to be higher when its neighbours have higher crime rates (e.g., Smith et al., 2000; Morenoff et al., 2001). This is consistent with a diffusion interpretation, which argues that the occurrence of crime in an area may increase the likelihood of crime in nearby areas. For example, a homicide in one neighbourhood may lead to a retaliatory killing in adjacent neighbourhoods (Cohen and Tita, 1999; Messner et al., 1999; Rosenfeld et al., 1999; Smith et al., 2000; Morenoff et al., 2001). Moreover, the spatial autoregressive coefficient  $\rho$  also incorporates the strength of spatial multipliers, as shown in equation (9), the effects from measured and unmeasured characteristics (i.e.,  $X$  and  $\epsilon$ ) of surrounding neighbourhoods that contribute to crime rates in the focal neighbourhood<sup>16</sup>. More specifically,  $\rho, \rho^2, \rho^3, \dots, \rho^m$  ( $m \rightarrow \infty, 0 < \rho < 1$ ) represent the rate at

<sup>16</sup> The  $\rho$  coefficient for the spatial lag term combines the spatial effects from all the measured independent variables  $X_s$  with those from the unmeasured characteristics (error terms) (Morenoff, 2003). To compare the relative

which the effects of a given neighbourhood characteristic spillover into surrounding neighbourhoods and decrease exponentially with each succeeding level of contiguity (i.e., the first-, second- neighbours and so on) (Morenoff et al., 2001).

Finally, the inclusion of spatial lagged terms in the models helped to further explain the between-neighbourhood variation in both types of crime. The “random effects” panel of Table 6.3 indicates that after adding the spatial lagged term, there was a substantive reduction from the empty model (Model 1 in Table 6.1) in the between-neighbourhood variance, 51% and 41% for violent crime rates and property crime rates respectively, compared to a value of 35% and 24% observed in the models that only included neighbourhood-level variables (Model 2 in Table 6.2). This indicates that a considerable amount of the variation in crime rates between neighbourhoods has been explained by the spatial effects arising from spatial interdependence among neighborhoods. Nevertheless, the variance components for both violent crime and property crime rates remained significant, indicating that some important factors that are missing from the models, such as individual-level characteristics as well as collective efficacy in neighbourhoods may influence neighbourhood differences in crime rates.

In summary, the results obtained from the spatial hierarchical linear models provide additional and valuable insight into the spatial dynamics of crime rates, by showing that crime rates in a given neighbourhood are not only dependent on the properties specific to that neighbourhood (its socioeconomic, demographic and dwelling characteristics) but also influenced by the

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contribution that each independent variable makes to the spillover effect (i.e., independent variables measured in nearby areas have an effect on a dependent variable in the focal area), it is better to estimate a model that contains spatial lagged independent variables  $WX$ , rather than spatial lagged dependent variable  $WY$  (i.e.,  $y = \beta X + \mu WX + \epsilon$ ) (Morenoff, 2003). However, we did not present the models here due to two practical constraints: 1) the relatively large number of neighbourhood-level independent variables ( $n=9$ ) may make such models not parsimonious, 2) some of the independent variables are strongly correlated with their corresponding spatial lagged terms, thus multicollinearity may be a significant problem if we include both simultaneously in the models.

characteristics of surrounding neighbourhoods, either through diffusion processes of criminal activities themselves or the spatial multiplier processes of social conditions related to crime.

#### **6.4. Model 4 - Controlling for City-level Characteristics**

The results presented thus far indicate that neighbourhood-level factors – including both contextual characteristics and spatial effects arising from interdependence among neighbourhoods – have essential impacts on the spatial distributions of crime and help explain a large amount of variation in crime rates across neighbourhoods. However, it is possible that the effects of these neighbourhood-level factors on crime may be affected or conditioned by the broader social climate that varies across cities. It has been shown that, when the city context is excluded from the analysis of neighbourhood crime, differences at the neighbourhood level are likely to be overestimated (Weijters et al., 2009). Therefore, the final analysis adds two city-level variables (i.e., city population and population per police officer)<sup>17</sup> to the level-2 equation of the hierarchical model in order to address the following three questions: (a) How do key features of cities – city size and police resources – influence crime rates of the neighbourhoods within them? (b) Does the inclusion of city-level variables alter the effects of neighbourhood-level factors on neighbourhood crime rates, as identified in the third model? (c) Does simultaneous analysis of the neighbourhood- and city-level factors further explain the city-level variance in neighbourhood crime rates?

Table 6.4 presents the full random-intercept models that include both neighbourhood-level and city-level variables. The “fixed effects” panel of the table provides a simultaneous estimation of

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<sup>17</sup> Although a variety of city characteristics can have impact on neighbourhood crime rates, the small sample size at level-2 (N=6) limited the number of city-level predictors that could be simultaneously included in the level-2 equation of multilevel models.

the effects of neighbourhood- and city-level factors –whether or not the effects at one social context or geographical level has attenuated the effects at another. The coefficient for the city-level variable is effectively an indication of the city-scale effect, over and above neighbourhood-level effects, because the level-1 independent variables are all grand-mean centered<sup>18</sup>. Despite being not statistically significant in this study, a marginal negative relationship was observed for both the city size (total population) and police resources (population per police officer) with each type of crime rate. It should be noted that the small number of level-2 units available for analysis (i.e., six cities) has resulted in reduced statistical power to detect significant effects, thus the statistical significance reported at level-2 (i.e., P-value in Table 6.4) might be more conservative than desired<sup>19</sup>.

Although the city-scale effect was not statistically significant in the current analysis, some tentative evidence can be found that the cities with larger population and larger police resources tend to have neighbourhoods with lower rates of violent and property incidents, independent of neighbourhood-level factors. The findings support the hypothesis that when all things are equal, city-wide public social control (by police forces) exerts a deterrence effect on neighbourhood-level crime rates by increasing the probability of being apprehended (Sampson and Cohen, 1988).

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<sup>18</sup> Grand-centering was adopted in the final models as our substantive focus was on the city-level effects, whether the city characteristics have separate, independent effects on neighbourhood crime rates net of the neighbourhood-level factors. As noted in Raudenbush and Bryk (2002), under grand mean centering, the intercept in the models represents the adjusted mean of outcome variable after controlling for the level-1 predictors. Accordingly, the regression coefficients associated with level-2 predictors represent the relationship between the level-2 predictor and the outcome variable less the influence of the level-1 predictors. It is true that grand-mean centering does not provide unbiased estimates of the pooled within group slopes for the level-1 predictors, but rather an ambiguous mixture of the within- and between-group slopes. However, this is less of a concern in this situation, given that our substantive interest in the current models was on the effects of city characteristics rather than the unbiased estimates of the neighbourhood-level relationships (as obtained in Model 2 and Model 3). It should be noted that group-mean centering does not control for the effects of level-1 predictors and consequently would be not appropriate in this situation.

<sup>19</sup> Raudenbush and Bryk (2002) suggest that the rule of thumb of 10 observations per predictor for a regression analysis can be applied to the hierarchical linear models with only a single level-2 outcome (e.g., a level-1 intercept term). In this case, the number of observations is the number of level-2 units (i.e., cities) and a sample of 10 cities is desired according to the 10-to-1 rule.

The small and negative effects of city population on neighbourhood crime rates may seem surprising, but they are in line with the city-level patterns that were previously observed (Figure 3.2): the largest cities in Canada (e.g., Montreal, Toronto) exhibited a general crime rate lower than that of smaller cities (e.g., Edmonton, Halifax, Saskatoon, Thunder Bay) during the last decade (1998-2009).

On the other hand, an examination of the fixed effects for neighbourhood-level variables indicates that the inclusion of city-level predictors had a relatively minor influence on the strength of the relationships between crime rates and neighbourhood-level variables as estimated in Model 3 (Table 6.3). All of the neighbourhood characteristics as well as the spatial lagged variables exerted almost the same effects on violent and property crime rates after controlling for city population and police recourses. Furthermore, by deviating each of the independent variables around their respective grand means, the intercept in the full random-intercept models provides an adjusted city mean for neighbourhood crime rates. That is, after controlling for compositional differences between cities in terms of neighbourhood characteristics (i.e., grand mean centers of the explanatory variables), the average neighbourhood crime rate across all the cities was 10 incidents per 1,000 residents for violent crime and 39 incidents per 1000 residents for property crime, as compared to the unadjusted mean of 12 and 47 incidents per 1000 residents estimated in the null model reported in Table 6.1.

In addition, the random effects for these models indicate that the inclusion of both neighbourhood- and city-level variables accounted for nearly all of the variation attributable to the city-level in neighbourhood crime rates (i.e., 91% for violent crime, 93% for property crime). Nevertheless, despite the relatively large portion of variation explained by these models, the

variance components for both violent and property crime rates remain significant, indicating that city differences in neighbourhood level crime rates were not captured entirely by the social contexts considered in the study.

**Table 6.4** - Full random-intercept models for violent and property crime rates

<b>Fixed Effects</b>	<b>Violent Crime Rate</b>		<b>Property Crime Rate</b>	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept (city mean neighbourhood crime rates)	9.617**	0.845	38.222**	2.892
<b>Neighbourhood-level Variables<sup>a</sup></b>				
Index of concentration at the extremes (ICE)	-0.480	1.338	-7.690*	3.449
Percentage of Aboriginal population	0.293**	0.047	0.788**	0.164
Percentage of dwellings built before 1961	0.006	0.006	--	--
Percentage of dwellings that require major repairs	--	--	0.332*	0.134
Percentage of lone-parent families	--	--	-0.089	0.081
Percentage of owned-occupied household	-0.040**	0.012	-0.048	0.040
Percentage of people who are single	--	--	0.040	0.066
Percentage of population aged 65 years and over	-0.084**	0.024	--	--
Percentage of recent immigrants	-0.031	0.025	-0.255**	0.086
Percentage of residents without high school diploma	0.058**	0.022	--	--
Residential stability	0.004	0.021	-0.114	0.069
Spatial lag term	0.792**	0.035	0.730**	0.035
Unemployment rate	0.223**	0.054	0.296	0.188
<b>City-level Variables</b>				
City population	-1.000E-06 (p= 0.427)	1.000E-06	-5.000E-06 (p=0.340)	4.000E-06



Population per police officer	-0.020 (p= 0.311)	0.017	-0.061 (p=0.358)	0.057
<b>Random Effects (Residual Variance)</b>	Variance Component	Variance Explained (R <sup>2</sup> )	Variance Component	Variance Explained (R <sup>2</sup> )
Between cities (level-2)	3.761**	91.317	43.577**	93.509
Within cities (level-1)	40.410	51.219	488.459	40.535
Deviation	9,754.611		13,407.203	

\*\*p<0.01, \*p<0.05

a. All neighbourhood-level and city-level predictors are grand-mean centered.

## 6.5. Summary

There is a rich tradition of research on how crime and social context are related (Van Wilsem, 2003). The relationships between crime rates and neighbourhood characteristics have been well documented in the crime literature (e.g., Shaw and McKay, 1942; Sampson and Groves, 1989; Elliott et al., 1996; Sampson et al. 1997; Bellair, 1997, 2000). However, previous research largely limited their analysis to one city and focuses exclusively on the internal properties of neighbourhoods while ignoring the wider social environment surrounding neighbourhoods. Using data from different Canadian cities, the analysis presented in this chapter improves on past research by considering social contexts not only in the local neighborhood but also in the wider spatial context within which that neighborhood is embedded – how both neighbourhood- and city-level contextual characteristics influenced neighbourhood crime rates, when spatial dependence among neighbourhoods are adjusted. Methodologically, this was accomplished by employing a series of multilevel models that incorporate spatial regression techniques.

Overall, the results from multilevel models provide rich insight into the research questions proposed at the beginning of this chapter. Firstly, one primary question is whether Canadian cities differ significantly with respect to their neighbourhood crime rates. The results indicate that neighbourhood crime rates varied significantly across the cities since the between-city variance was greater than 0 and was statistically significant (i.e.,  $\tau = 43.314$  for violent crime

rates, 671.291 for property crime rates,  $P < 0.001$ ). Although most of the variance in neighbourhood crime rates was attributed to differences within cities rather than between cities (i.e., 66% for violent crime, 55% for property crime), city-level factors could at most account for 34% of the total variance in neighbourhood violent crime rates, 45% in the case of property crime. These findings lead support to the hypothesis that city context matters in determining crime rates of a given neighbourhood, particularly in the Canadian context.

A second key goal of our multilevel analysis is to assess across the cities studied, how crime rate in a neighbourhood is related to the local characteristics specific to that neighbourhood. One major advantage of hierarchical linear models (HLM) over traditional single-level models is they allow an unbiased estimation of the pooled within-city relationship between neighbourhood crime rates and neighbourhood-level contextual variables by isolating the between-city differences. The results suggest that when city random effects are controlled, certain socioeconomic, cultural, demographic and dwelling characteristics of neighbourhoods are significantly associated with neighbourhood crime rates. Across the cities under study, when all neighbourhood characteristics available in this study are held constant, six characteristics significantly contribute to the variance in neighbourhood violent and property crime rates. More specifically, both violent and property crime rates tended to be higher in neighbourhoods where there was a larger proportion of Aboriginal people and higher unemployment rate, while generally lower in neighbourhoods with higher affluence and residential stability, and those with a greater proportion of recent immigrants and owner-occupied households. Furthermore, both types of crime rate were significantly associated with deteriorated physical environments at the neighbourhood level though differed in specific ways: neighbourhoods with a higher proportion of dwellings that require major repairs tended to be more vulnerable to property offences,

whereas violent crime was likely to be prevalent in neighbourhoods with older dwellings (built before 1961). Despite these similarities, violent crime rates were also positively related to the proportion of people with no high school diploma, while negatively associated with the proportion of elderly people (aged 65 and over). However, property crime rates tended to be higher in neighbourhoods where there was a larger proportion of single population.

In light of these findings, our multilevel results provide strong evidence for social disorganization theory, which suggests that social stress indices such as low education attainment, unemployment rate, degradation of the physical environment significantly contribute to higher crime rates in a neighbourhood, while other social control variables such as residential stability, house ownership, and concentrated affluence have a protective effect against crime. On the other hand, these findings are consistent with two hypotheses derived from routine activity theory: one is that single people are generally younger and more frequently participate in evening activities and thus more at risk of being involved in criminal incidents (Hirschi and Gottfredson, 1983; Land et al., 1990); and another is that the lifestyles of elderly people (e.g., home-centered daily activity) enable them to be present at home more frequently and inadvertently guard over neighbourhoods, which potentially has a protective effect against crime (Charron, 2008).

Concerning the findings that the proportion of Aboriginal people and the proportion of recent immigrants influenced neighbourhood crime rates in the opposite direction, our results provide little evidence to the argument from social disorganization theory, which states that cultural heterogeneity of a neighbourhood is associated with crime since it is presumed diverse normative and linguistic terms that might inhibit community cohesion (Shaw and MacKay, 1942; Elliot et al., 1996). However, our results are in line with those of many Canadian studies, which found similar relationship between crime and the percentage of Aboriginal people or recent immigrants

(e.g., Savoie, 2006; Savoie, 2008a, 2008b; Charron, 2008, 2009). At the very least, these findings suggest the need to improve the measure of ethnic heterogeneity (e.g., the diversity of ethnic groups) in a neighbourhood and to consider potential benefits of cultural diversity in the Canadian context.

In addressing the research question of whether crime rate in a given neighbourhood is related to characteristics of adjacent neighbourhoods, this chapter demonstrates the need to consider spatial dependence of crime when examining the relationship between neighbourhood characteristics and crime rates. As noted earlier, the spatial autocorrelation analysis (Chapter 5) indicates that within each city under study, violent and property crime rates showed significant spatial dependence among neighbourhoods. This provides strong justification for further exploration of such spatial effects at the neighbourhood level. For this purpose, we introduced spatial lagged versions of the dependent variable (the weighted average of violent/property crime rates in neighbouring locations) as an additional level-1 independent variable (besides other neighbourhood contextual variables) in the hierarchical linear models. The results indicate that the observed spatial dependence in neighbourhood crime rates persisted even after the neighbourhood-contextual predictors of crime have been accounted for (i.e., regression coefficient of spatial lag term is 0.78 for violent crime and 0.72 for property crime,  $P < 0.01$ ).

Furthermore, for both types of crime, the introduction of a spatial lag term in the hierarchical models reduced some of the neighbourhood contextual effects to become insignificant and diminished the magnitude of those that remained significant. Therefore, there is a reason to believe that the ecological impact of these neighbourhood characteristics on local crime rates may be partially due to the spatial interdependence of neighbourhoods. In short, by taking spatial dependence into account, the multilevel results advance our knowledge of neighbourhood crime,

such that crime rate in a given neighbourhood is not solely depend on specific characteristics of the neighbourhood itself, but instead on those of surrounding neighbourhoods.

Finally, this chapter also assesses whether wider social contexts, such as the city, have an impact of their own on neighbourhood crime rates. This was done by relating two city-level characteristics, namely, city size (i.e., total population) and public social control exercised by police forces (i.e., population per police officer), to neighbourhood rates of crime, while adjusting for compositional (neighbourhood) differences. Neither of them displayed statistically significant effects on violent and property crime rates ( $P > 0.1$ ). The statistically insignificant influences of city-level variables on violent and property crime rates may be partially due to the small sample size at level two of the analysis (i.e., six cities), resulting in reduced power to reveal significant findings. Nonetheless, the overall pattern of the results, suggests that city context has an independent effect on neighbourhood crime rates, such that neighbourhoods embedded in cities with a smaller population and fewer police resources may have higher crime rates, after taking neighbourhood-level factors into account. The observed city-level effects support the assumption that social contexts beyond and external to neighbourhoods are relevant for understanding local variations in crime rates.

In conclusion, the results from multilevel models indicate that for the cities under study, crime rate in a neighbourhood is not only dependent on social conditions specific to that neighbourhood (i.e., its socioeconomic, demographic and dwelling characteristics), but also on the characteristics of surrounding neighbourhoods as well as broader city environments. This is an improvement over previous neighbourhood crime research, which has primarily focused on the internal characteristics of neighbourhoods to explain crime rates. Our findings suggest that the understanding of social contextual effects on crime can be improved by including multiple

social contexts instead of solely the neighbourhood and by taking neighbourhood spatial dependency into account.

## **Chapter 7 Discussion and Conclusion**

This study examined the spatial patterns of crime across urban neighbourhoods in six Canadian cities and explored the contextual effects of social environments (e.g., neighbourhood socioeconomic and demographic characteristics, social control exerted by city police forces) on these distributions. Exploratory spatial data analysis (ESDA) and multilevel modelling techniques were employed in this analysis of crime and social contexts. Our analyses yielded several noteworthy findings that provide empirical answers to the research questions and suggest interesting avenues for future research. This concluding chapter summarises the results of this study by answering the original research questions posed by this thesis, including (1) how are police-reported criminal incidents distributed across neighbourhoods within the Canadian cities? (2) How can we quantify the relationship between crime rates and their associated neighbourhood factors, such as its socioeconomic, demographic, and dwelling characteristics? (3) Is the crime rate in a neighbourhood influenced by nearby neighbourhoods? (4) Do wider social contexts, such as at the city level, have an impact on neighbourhood crime rates?

The remainder of this chapter is divided into two parts. The first part reviews the empirical findings of this research. The second part discusses implications of this research and the direction for further analyses. First, limitations related to the data and methods used in this study are discussed and suggestions are given on how improvements can be made in these respects. Some interesting paths for future are also discussed. The chapter then concludes with some implications for crime prevention policy based on the results found in this study.

## **7.1. Summary of empirical findings**

### **7.1.1. Spatial Patterns of Crime across Canadian Urban Neighbourhoods**

The first research question investigated in this study is how police-reported criminal incidents are distributed across urban neighbourhoods in six Canadian cities. An exploratory spatial data analysis (ESDA) approach was adopted involving data visualization and spatial autocorrelation analysis. Data visualization by means of box maps and box plots were useful for exploring the general characteristics of the spatial distribution of crime in the six cities studied. Spatial autocorrelation analysis was used to identify significant spatial clustering in the crime datasets. The results of ESDA revealed several interesting patterns and trends that are worthy of attention. The main similarities and differences of the six cities in the spatial patterns of crime are further discussed below.

First, some general trends in the spatial patterns of crime across urban neighbourhoods can be found. The mapping of crime indicated that both violent and property crimes (reported to the police) are not distributed equally or randomly in the Canadian cities. They are, instead, often concentrated in particular neighbourhoods that occupy a relatively small proportion of a city's geographic area. Overall, in all of the Canadian cities examined, high crime neighbourhoods were largely found in the inner city with noticeable concentrations around the city centers. By comparison, moderate and low crime neighbourhoods were more likely to occur in peripheral zones close to the city boundaries. These findings are in accordance with the "concentric zone model" from the Chicago School's urban studies (Park and Burgess, 1925), which suggests that cities tend to expand from the center and form five concentric zones, and it is the "zones in



transition” located around the city centre that experience most social and physical deterioration and higher rates of social problems, including crime.

Furthermore, results from the spatial autocorrelation analysis confirmed the non-randomness in the spatial distribution of violent and property crime rates across urban neighbourhoods, supporting the conclusion that spatial dependency is significant. The global Moran’s I statistic was positive and significant for each city’s crime dataset, violent and property crime rates respectively, providing strong evidence of an overall spatial clustering of similar crime rates within each city under study. Further examination of local patterns of spatial autocorrelation using the local Moran’s I statistic and LISA cluster maps offered further specific insight into the local variation in spatial dependence and revealed considerable city differences. For example, some cities (e.g., Halifax, Thunder Bay) exhibited a single cluster of high crime neighbourhoods that was exclusive to the urban center. Other cities (e.g., Montreal, Toronto) showed multiple clusters of crime hotspots that were scattered throughout the city, rather than being constrained to the city center. More specifically, the six cities can be grouped into three categories based on the local patterns of spatial autocorrelation of crime rates.

Halifax and Thunder Bay exhibited a similar pattern showing to a great degree the trend of crime being mostly concentrated in the city center. For both violent and property crime, there was only a single, centralized cluster of high crime neighbourhoods that was located around the downtown core of these two cities. By contrast, the clusters of low crime neighbourhoods appeared towards peripheral zones or suburban areas of the cities. The majority of neighbourhoods located in the transition zone between the urban center and peripheral areas were either not significantly clustered (spatially random) or considered to be spatial outliers (negative spatial autocorrelation) in terms of their crime rates. This observed pattern provided evidence consistent with a diffusion

process, demonstrating that in general, crime shifts away from the original innovative node (i.e., the urban core) in a form of outward moving “fringe” (Messner et al., 1999) with the intensity diminishing with increasing distance to the city center.

The cities of Edmonton and Saskatoon showed a second pattern that showed tight clustering of high violent crime neighbourhoods almost all located in the inner city area. On the other hand, high property crime rates tended to cluster closely, not only in neighbourhoods around the city centre but in certain city’s suburban neighbourhoods. Previous research has found that the concentrations of property crime hotspots outside the city center were located around large shopping centers, megastores and commercial strips (Savoie, 2008a, Charron, 2008). Again, both low violent and property crime neighbourhoods were significantly clustered in peripheral zones close to the city boundaries. In addition, another distinguishing feature of the geography of crime in Edmonton and Saskatoon is that spatial distributions of crime rates, which were different between the two sides of the city’s main river. In Saskatoon, violent and property crime rates were generally higher in neighbourhoods located west of the South Saskatchewan River compared to those east of it. In Edmonton, neighbourhoods located north of the North Saskatchewan River generally experienced higher violent and property crime rates. There appear to be regional differences within the city imposed by the presence of large physical features (e.g., river). This implies that, physical barriers such as a river that separates two places may provide a break in the spatial organization of crime since access to each side is limited and also divide neighbourhoods with individual characteristics. Future research may explore such disparities further, although the role of physical barriers is not a primary focus of this study and not discussed further here.

The third pattern was observed in Montreal and Toronto, where both violent and property crime rates showed multiple hotspots of spatial clustering dispersed throughout the city, rather than constrained to the city center. Similarly, significant clustering of low crime rates extended beyond peripheral areas and were primarily associated with several inner city neighbourhoods. In addition, violent and property crime differed markedly with respect to their spatial distributions in both of these two cities. Although both violent and property crime rates highlighted neighbourhoods around the city center as a significant spatial cluster, they exhibited different local patterns of spatial autocorrelation. The areas where high violent crime rates were clustered did not always correspond to the concentrations of high property crime rates and vice versa. This is different from what was observed in the other four cities (Edmonton, Saskatoon, Halifax, Thunder Bay), where violent and property crime rates in general followed somewhat similar patterns in the topology of spatial associations. In brief, the police-reported crime rates in Toronto and Montreal presented a more intricate spatial organization than that observed in other smaller cities. This result suggests that the complex urban structure and social geography of larger cities, such as Toronto and Montreal may play a critical role in the spatial distribution of crime. For example, both Montreal and Toronto have several separate clusters of low-income neighbourhoods not exclusive to the urban core, but scattered throughout the suburbs (Heisz and McLeod, 2004). A Lack of material and political resources held by the residents of disadvantaged neighbourhoods results in a collective inability for internal organization and exerting social control, which, in turn, may increase opportunities of crime occurring in these areas (Sampson et al.,1997; Van Wilsem, 2003). Likewise, there are also several clusters of commercial activity spreading out in many areas within the two cities, including not only the downtown areas, but also some large shopping centres and commercial streets. According to

routine activity theory (Cohen and Felson, 1979), large concentrations of commercial activities tend to attract many people to a single location and create an environment of intense human activity, thus providing increased opportunities for crime. In addition, in large urban areas such as Montreal and Toronto, the public transit system makes a pronounced impact on travel (Charron, 2009). There are several transportation zones throughout the city, which have many public transit routes (e.g., subway, train stations, bus stops) covering and large numbers of people travelling through. Given the routine activity framework, the high accessibility of these areas may increase the number of motivated offenders and potential victims, as well as create an anonymous setting that might be favourable to crime. All of the scenarios above may help explain why several significant clusters of high crime rates occurred beyond the city centre in these two cities.

In summary, the results obtained from the ESDA in Chapter 5 offer critical insight into the spatial patterns of crime in the six Canadian cities: Crime was not distributed uniformly or randomly in urban areas. Within the individual cities investigated, it was also observed that crime tends to be concentrated in particular neighbourhoods that occupy a relatively small proportion of the city's geographic area. Both neighbourhood violent and property crime rates exhibited significant spatial autocorrelation. On the other hand, some differences between the cities regarding the distributions of crime across neighbourhoods were noted. In short, these findings collectively support the hypothesis that the Canadian urban system is characterized by considerable regional variation, and thus, the geography of crime is also likely to vary markedly not only within cities, but also between cities (Savoie, 2008b).

### **7.1.2. Multilevel Analysis of Crime and Social Contexts**

One main goal of this study is to investigate how the variance in neighbourhood crime rates can be accounted by the social contextual characteristics. Since the data consist of a two-level hierarchy with neighbourhoods nested within cities, the relationship between crime rates and social contextual characteristics were formally quantified by using multilevel modelling techniques. Specifically, neighbourhood violent and property crime rates were modelled over multiple scales of analysis, as a function of both neighbourhood- and city-level contextual variables, respectively. In addition, by incorporating spatial econometric techniques into the multilevel models, the robustness of these contextual predictors of crime rates was tested with rigorous controls for spatial dependence. The results from multilevel models suggested that internal characteristics of neighbourhoods, neighbourhood spatial interdependence and city characteristics are each important for understanding neighbourhood-level variances in rates of crime. The main findings from multilevel analysis are interpreted and summarized below in three sections, discussing results obtained from each of the three effects.

#### **7.2.1.1. Neighbourhood Characteristics and Crime Rate**

In answering the research question, results of multilevel models suggested that the crime rate in a neighbourhood was attributable to factors that are specific to that particular neighbourhood. Some of the socioeconomic, cultural, demographic and dwelling characteristics of neighbourhoods examined in this study were significantly associated with neighbourhood crime rates, after controlling for city-random effects.

#### **7.2.1.1.1. Socioeconomic Characteristics of Neighbourhoods**

Across the cities examined, both violent and property crime rates tended to be higher in neighbourhoods with higher unemployment rates and a smaller proportion of affluent households (measured by the ICE index). High violent crime rates were also concentrated in neighbourhoods where residents had lower education attainment (i.e., the proportion of residents without high school diploma). Each of the three variables seems to cover a specific aspect of neighbourhood residents' access to socioeconomic resources, which determine their collective ability to mobilize resources to exert social control and prevent crime. Thus, in support of social disorganization theory and strain theory (Shaw and MacKay, 1942; Merton, 1938), the findings indicate that limited access to socioeconomic resources or inequality of socioeconomic resources among neighbourhoods may prevent residents from mobilizing resources against crime problems.

The level of education and employment status provide a partial, indirect measure of a neighbourhood resident's ability to obtain income from stable paid employment (Charron, 2009). Our results presented here do not necessarily entail that these individual features of residential population (low education level and unemployment) are the primary causes behind higher crime rates in their neighbourhoods. Rather, the findings bear out the claim that limited access to material (socioeconomic) resources compromises adherence to the standards of behaviour endorsed by society in general, thus creating a setting that is conducive to the perpetration of criminal incidents (Massey, 1996; Body-Gendrot, 2001; Forrest and Kearns, 2001; Bauder, 2002; Sampson et al., 2002; Charron, 2009). In addition, the inadequacy of material resources held by neighbourhood residents results in a collective inability for internal organization and exerting social control (Sampson et al., 1997; Van Wilsem, 2003). Based on the routine activity theory,

this condition may offer more opportunities presented to offender when they interact with potential targets (Cohen and Felson, 1979).

The negative association found between the ICE index with neighbourhood violent and property crime rates are consistent with findings obtained by Sampson et al. (2001), Massey (2001), and Cahill and Mulligan (2007) which suggest that concentrated affluence tends to produce a separate set of protective mechanisms to reduce negative outcomes (e.g., disorder, crime) net of neighbourhood disadvantaged conditions (e.g., poverty, family disruption). Affluent neighbourhoods may be more able to mobilize collective resources to exert social control and achieve common goals (e.g., local safety), which consequently mitigates crime problems. It is also noteworthy that the proportion of low-income households<sup>20</sup>, an absolute measure of economic disadvantage, did not have a significant effect on neighbourhood crime rates. Recall that the ICE index represents the degree of concentrated affluence relative to the concentration of poverty in a neighborhood and thus captures relative inequality in a community. This offers limited support for the hypothesis from strain theory (Merton, 1967; Blau and Blau, 1982) that the relative deprivation caused by unequal distribution of material resources creates a setting conducive to the perpetration of crime (Blau and Blau, 1982).

#### **7.2.1.1.2. Ethno-Cultural Characteristics of Neighbourhoods**

Two measures of the ethnocultural composition of neighbourhoods, namely, the proportion of Aboriginal population and recent immigrants, were found to have a significant impact on neighbourhood rates of violent and property crimes, but the direction of these effects differed. In particular, the proportion of Aboriginal emerged as the most robust predictor of neighbourhood

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<sup>20</sup> Percentage of low-income households was included along with the ICE measure, as well as other neighbourhood-level variables in the initial estimation of Model 2. But it was dropped later due to its statistically insignificant effect.

crime rates, as its effects remained after controlling for spatial dependence and the potentially confounding city-level covariates. The over-presentation of Aboriginal people as victims and offenders has been well documented in Canadian research over the last several decades (e.g., Richards, 2001; La Prairie, 2002; Brzozowski et al., 2006; Savoie, 2008b). According to the 2004 General Social Survey (GSS) on victimization, Aboriginal people reported experiencing violent victimization at a rate that was about three times higher than that of non-Aboriginal people (Gannon and Mihorean, 2005). Aboriginal people were also highly overrepresented as offenders charged in police-reported homicide incidents based on the homicide survey (11.2 accused persons per 100,000 Aboriginal population compared to 1.1 accused persons per 100,000 non-Aboriginal population conducted between 1997 and 2000) (Brzozowski et al., 2006). Efforts to understand high Aboriginal victimization and offending have considered a variety of potential sources, including discrimination within the criminal justice system (Roberts and Doob, 1997), as well as the conflict between Aboriginal and non-Aboriginal cultures (Hartnagel, 2000).

The growing size of urban Aboriginal populations along with their higher distribution in inner-city neighbourhoods in recent years have led researchers to examine the potential impact of Aboriginal living conditions, especially social and economic conditions of neighbourhoods, to their over-representation as victims and offenders (e.g., Fitzgerald and Carrington, 2008). There is evidence that Aboriginal populations residing in large Canadian cities tend to face greater challenges than non-Aboriginal populations in terms of lower levels of personal income, educational attainment and employment, as well as higher rates of lone-parent family structures and residential mobility (Richards 2001; La Prairie, 2002; Fitzgerald and Carrington, 2008). It has been found that Aboriginal people are disproportionately more likely to live in the most socio-



economically disadvantaged areas, which in turn may partially explain the elevated level of police-reported Aboriginal crime, since these areas also have the most police enforcement and reporting (Fitzgerald and Carrington, 2008). Such findings are strongly supported by the results from this study, showing that higher crime rates in neighbourhoods with a larger proportion of Aboriginal populations may be at least partially attributed to disadvantaged living conditions of neighbourhoods where Aboriginal people are more likely to reside<sup>21</sup>.

By comparison, the percentage of recent immigrants (defined as those arriving in Canada during the 10 years preceding the census) was inversely proportional to both types of crime rates at the neighbourhood level. That is, neighbourhoods with greater concentrations of recent immigrants generally had lower crime rates when all other factors were considered equal. As with the findings related to Aboriginal population, recent immigrants represented a disproportionate share of the low-income population in Canada and were more likely than other groups to live in low-income neighbourhoods (Heisz and McLeod, 2004). Despite their lower income, however, the proportion of recent immigrants seems to have a protective effect on crime in neighbourhoods.

Several important features of recent immigrants in Canada can shed additional insight on this finding. First, for most newly landed immigrants, family and social networks are primary considerations in the decision of where to live (Heisz, 2006). Therefore, new immigrants tend to settle in urban neighbourhoods where co-ethnic communities have been formed by earlier

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<sup>21</sup> In order to examine the contribution of neighbourhood socioeconomic conditions to the relationship between crime rates and Aboriginal residential populations, we re-estimated the model 2 in Table 4.2 with the proportion of Aboriginal populations as the only predictor variable. The result confirmed the strongly positive association between crime rates and the proportion of Aboriginal population at the neighbourhood level. The percentage of Aboriginal population itself, in fact, has accounted for a considerable portion of the within city variance in neighbourhood crime rates (i.e., 47% for violent crime, 14% of property crime). A comparison between the result of this bivariate model and that of the multivariate model (Table 4.2) indicates that when indicators of neighbourhood socioeconomic disadvantage were adjusted for (e.g., income equality, unemployment, low education attainment), the strength of the association between the percentage of Aboriginal population and neighbourhood crime rates has reduced by 34% for violent crime and 31% for property crime but both remained significant.

immigration. The co-ethnic neighbourhoods provide emotional, social and cultural support as well as other resources such as housing, information sharing and labor market opportunities for newly arrived immigrants, which can help them more quickly to integrate into the host society (Graif and Sampson, 2009; Herzog, 2009). As for newly settled immigrants themselves, within unfamiliar environments, they are less likely to be involved in any activity that would put them at risk, degrade their reputation or jeopardize their status. Instead, they tend to abide by the law in order to protect their legal immigration status. Moreover, the common acceptable code of ethics shared among co-ethnic immigrants may operate as an informal social control on illegal activities (Martinez, 2006). In addition, the arrival of new immigrants may serve as a catalyst for neighbourhood revitalization, such as increasing the demand for housing and employment, attracting business investment, establishing social and cultural institutions, which when taken together, may lead to an overall enhancement in well-being and reduce the likelihood of disorder and crime (Herzog, 2009). Finally, low economic status of recent immigrants (refer to Heisz and McLeod, 2004 for more detail) may indicate low availability of valuable targets that are attractive to offenders compared to other affluent neighbourhoods inhabited by high-income residents.

#### **7.2.1.1.3. Demographic Characteristics of Neighbourhoods**

In comparison with socioeconomic and cultural characteristics, demographic characteristics of neighbourhoods were only slightly associated with crime in the cities examined. Nevertheless, residential stability (measured as the proportion of residents living at the same address in the last 5 years preceding the census) and percentage of owner-occupied household showed significantly dampening effects on both violent and property crime rates in neighbourhoods. According to social disorganization theory, high residential mobility and being a renter may limit one's

attachment to one's own neighbourhood in which they reside and does not favour the development of social network and social control of criminal behavior (Pain, 2000; Brown et al., 2004; Charron, 2009). In contrast, in neighbourhoods where people tend to live at the same address for an extended period and with greater proportions of owner-occupied dwellings, the residents tend to have a strong sense of belonging to their local community and may be more willing to participate in long-term schemes for crime prevention. This result is consistent with findings from previous studies that found that neighbourhoods where residents are familiar with each other or feel responsible for their community tends to significantly lower rates of violence compared to those where social cohesion is low (e.g., Sampson and Groves, 1989; Boggess and Hipp, 2010).

The proportion of elderly people was only negatively associated with violent crime rates at the neighbourhood level. This finding may reflect the fact that most people aged 65 and over tend to stay at home for lengthier periods than the young, and thus are more likely to informally watch over their neighbourhood (Charron, 2009). Given the routine activity framework, frequent residential occupancy or even immobility of elderly people can act as a deterrence against crime. By contrast, the proportion of single population was found to be positively related to property crime rates. This result is partly due to the fact that single people are generally younger and more frequently participate in evening activities (e.g., going to bars and nightclubs), which, according to routine activity theory, is likely to place them at higher risk of being either offenders or victims of crime (Hirschi and Gottfredson, 1983; Land et al., 1990).

However, apart from these findings, an unexpected result indicated that the proportion of single-parent families showed a slightly negative association with property crime rates. This is opposite to the claim of social disorganization theory, where family disruption is linked to decreased

guardian and supervision of children, and thus concentrations of single-parents in an area may place adolescents at higher risk for delinquency (Sampson and Groves, 1989). The unexpected finding was in part due to the problem of multicollinearity, as indicated by the high correlation between the two variables: the proportion of single population and the proportion of lone-parent families ( $r = 0.426$ ,  $p < 0.05$ ). In fact, the effects of single-parent families became insignificant when the proportion of single population was dropped from the multilevel models.

#### **7.2.1.1.4. Dwelling Characteristics of Neighbourhoods**

The findings from this study supported the hypothesis driven from broken window theory that degradation of the physical environment promotes criminal behavior (Kelling and Coles, 1996). Particularly, the results indicated that neighbourhoods with a larger proportion of dwellings that require major repairs tend to be more vulnerable to property offences, while violent crime was especially prevalent in neighbourhoods with older dwellings (built before 1961). The presence of run-down buildings do not necessarily have a direct cause-effect with crime rates, but they are indicators of the deterioration of underlying physical conditions, which may lead to a general sense of not caring and ambivalence to one's own neighbourhood. This may result in further degradation of social cohesion within the community and create a setting that is conducive to crime (Brown et al., 2004; Charron, 2009).

#### **7.2.1.2. Neighbourhood Spatial Dependence and Crime Rate**

One distinctive methodological feature of this study is the combination of multilevel and spatial modelling techniques. Statistically, it allowed us to take spatial dependence into account when examining the relationships between crime and contextual characteristics measured at both neighbourhood and city levels in order to obtain more accurate estimates. More importantly, we were able to address the research question of whether crime rate in a given neighbourhood is

influenced by characteristics of nearby neighbourhoods. As noted earlier, the spatial autocorrelation analysis revealed that within each city under study, violent and property crime rates showed significant spatial dependence among neighbourhoods: Crime at proximal neighbourhoods appeared to be correlated, either positively or negatively. This was an initial indication that neighbourhoods were interdependent and that there might be spatial effects present in the crime data warranting further investigation. Therefore, in the multilevel models, we formally estimated spatial dependence effects by introducing spatial lagged versions of the dependent variable, the weighted average of violent/property crime rates in neighbouring locations, as an additional level-1 (neighbourhood-level) independent variable (besides the other neighbourhood contextual variables). Such models allowed an estimation of the independent effect of spatial dependence on neighbourhood crime rates, accounting for the neighbourhood contextual characteristics.

The results indicated that the observed spatial dependence in neighbourhood crime rates persisted even after controlling for the neighbourhood-contextual predictors of crime (the neighbourhood socioeconomic, demographic and dwelling characteristics discussed above), since the correlation between the crime rate of a focal neighbourhood and the corresponding average value of its adjacent neighbors was estimated to be as high as 0.78 for violent crime and 0.72 for property crime (i.e., regression coefficient of spatial lag term). This result suggested that crime rates in a given neighbourhood did not solely depend on the characteristics of the neighbourhood itself, but instead on those of adjacent neighbourhoods. In fact, our estimates of spatial effects were quite large in magnitude. In the six cities under study, spatial effects were stronger than any other neighbourhood characteristic when explaining the distribution of crime across neighbourhoods (i.e., the largest standardized coefficients were recorded among all the

explanatory variables included). Moreover, the spatial dependence effects significantly moderated the impact of internal neighbourhood characteristics on a neighbourhood's crime rate. For both types of crime, the introduction of a spatial lag term in the hierarchical models reduced some of the neighbourhood contextual effects to becoming insignificant and diminished the size of those that remained significant. It appears that the contextual effects of these neighbourhood characteristics on local crime rates can be partially dependent on the spatial interdependence of neighbourhoods.

These findings may reflect the fact that some criminal incidents can diffuse over space such that crime in one neighbourhood is likely to increase the likelihood of future crime in proximate neighborhoods. This may be partially explained by a process of social transmission – community members are likely to imitate behavioral patterns prominent in nearby places, and as such acts of violence may spill over to surrounding areas (Cohen and Tita, 1999; Sampson et al., 1999). Or perhaps several types of crime (e.g., homicides) are retaliatory in nature and thus crime that occurs in one neighborhood may instigate retaliatory acts in a nearby neighborhood (Kubrin and Weitzer, 2003a).

In addition, the findings also imply potential spatial processes operating in the social contexts related to crime, such as crime-inducing or -reducing circumstances that may spill over multiple neighbourhoods to exert external influences beyond the local neighbourhood. According to routine activity theory, motivated offenders tend to search for criminal opportunities between homes, hangouts or other key locations in their daily activities (Brantingham and Brantingham, 1984). From this perspective, a neighborhood's "exposure" to the risk of crime may be heightened by its spatial proximity to places where potential offenders live (Morenoff et al., 2001). Given the perpetration of criminal incidents may be associated with several

neighbourhood characteristics such as poverty, high residential mobility and ethnic heterogeneity, spatial proximity to these crime-inducing factors in nearby neighbourhoods is likely to increase the risk of criminal victimization in a focal neighbourhood (Cohen and Tita, 1999; Sampson et al., 1999). On the other hand, the development of social capital and collective efficacy in a neighbourhood may benefit not only residents of that area but also others who live nearby (Sampson et al., 1999). Therefore, a neighbourhood may benefit by its proximity to areas with higher levels of social capital and collective efficacy, since such social processes can go beyond the immediate neighbourhood to exert overarching effects.

Although the results presented here have yet to allow a distinction between these two sources of dependence, our analyses nevertheless lend credibility to the claim that neighbourhoods are spatially interdependent parts of a broader social system (e.g., city), which has been long recognized in urban sociology and geography, but largely ignored in empirical applications in social science research (Morenoff, 2003). Our findings call into question the conventional approach of studying neighbourhood effects that focus solely on the internal properties of neighbourhoods that may arrive at fallacious conclusions, since they are missing the potentially important contextual influence of interactions between neighbourhoods within their wider social environment.

### **7.2.1.3. City Contextual Characteristics and Crime Rate**

Our multilevel analysis also included an examination of whether city-level conditions, as indicated by city size (i.e., total population) and formal control exercised by police officials (i.e., population per police officer), influenced neighbourhood crime rates over and above the neighbourhood-level characteristics and spatial dependence effects. Although a small sample size of six cities made it difficult to detect a significant effect at the city level, some tentative

conclusions can still be drawn from the results of this study. Namely, the city context may have an impact of its own on neighbourhood crime rates, such that neighbourhoods embedded in cities with a smaller population and fewer police resources may have higher crime rates, after effects of neighborhood-level factors have been taken into account. The observed city-level effects support the hypothesis that wider social contexts as large as cities are relevant for understanding neighbourhood differences in crime rates (Van Wilsem, 2003).

These results have two important implications for the city contextual effects on crime rates.

First, cities of different sizes tend to have varying social and economic conditions and different population profiles, which may collectively play a role in the distribution of neighbourhood profiles within the city, including the neighbourhood variance in crime rates. Second, city-wide public social control (e.g., local police) may be another potential source of contextual effects that extend beyond neighbourhood boundaries. As cities may differ in allocating government resources for crime prevention or reduction, there are differences in the extent to which residents in a given neighbourhood can utilize external resources beneficial to the maintenance of local public safety (Van Wilsem, 2003). These results were consistent with previous work done by Buisck and Grasmick (1993), who suggested that neighbourhood order cannot be understood merely through the internal capacity for organization, rather it also depends on the availability of external resources for social control (Van Wilsem, 2003). Importantly, these findings expand on social disorganization theory (Shaw and McKay, 1942), which has primarily focused on the internal characteristics of neighbourhoods to explain crime rates. More detailed exploration into these two types of contextual effects that extend beyond the immediate neighborhoods may represent one intriguing direction for future research.



In summary, a review of the multilevel results reveals that for the cities under study, the crime rate in a neighbourhood is not only dependent on the local characteristics of the neighbourhood itself, but also on the characteristics of surrounding neighbourhoods and broader city characteristics. These findings suggest that our understanding of social contextual effects on crime can be improved by including multiple social contexts instead of solely neighbourhood characteristics, while taking neighbourhood interdependency into account.

## **7.2. Limitation and Future Work**

Apart from providing empirical answers to our research questions, this study has some limitations that need to be acknowledged when interpreting the results. One of the limitations of this study may result from the use of secondary aggregated data on crime and contextual characteristics, where no information is provided about the detailed background of offenders and victims involved or the situation in which the crime occurred. It should be appreciated that individual variance in personal attributes may be concealed in the process of aggregating data (Chainey and Ratcliffe, 2005). Thus, inferences drawn about the characteristics of an individual based on aggregated data are likely to be affected by issues related to the ecological fallacy (Robinson, 1950). The ecological fallacy can occur when an inference is made about the nature of specific individuals based solely upon aggregated statistics collected for the group to which those individuals belong (Robinson, 1950). Therefore, crime rates and aggregate population characteristics observed at either neighbourhood or at the city level do not necessarily reflect individual characteristics that are related to offending or victimization, which may potentially limit our interpretation of results from this study. Another issue related to aggregation of data sources is the potential impact of the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984), which identifies that any geographic aggregation processes, such as the count of crime within

geographical units, may be as much a function of the size, shape and orientation of the geographic areas themselves (Openshaw, 1984). From this perspective, the spatial distributions of crime observed from this study might be influenced by both the various sizes of census tracts and the corresponding geographic boundaries.

Second, this study relies on police registration data, which may potentially contain some problems that constrain their use for assessing the relationship between crime and social contexts. One main drawback of official crime data is that they include only crime reported to and recorded by police officials, yet many crime incidents may not come to the knowledge of the police (Wittebrood and Junger, 2002). There are many factors influencing police-reported crime data, such as underreporting, changes in legislation, and policies or enforcement practices (Charron, 2009). Underreporting is the most significant problem, which is mainly due to the unwillingness or inability of the public to report crime to the police. British Crime Survey (BCS) estimates that only about 42% of crimes that happen have actually been reported to police (Chainey and Ratcliffe, 2005). This may partially results from the fact that victims feel that some crimes are not very serious or that they do not require any further police or court intervention (Goudriaan et al., 2006). Or perhaps some victims, especially those belonging to vulnerable groups (e.g. the poverty, minorities) have limited access to the police service or other public security facilities. Furthermore, if victims' reporting behaviour depends in part on their position in society or associated with crime-related social conditions, then the distribution of crime unknown to police may vary across social contexts (Van Wilsem, 2003). For example, it has been shown that residents of neighbourhoods with extreme socio-economic disadvantage have less social interaction and tend to have less confidence in police effectiveness, reducing the probability of reporting crime to the police (Goudriaan et al., 2006). If neighbourhoods differ in

their willingness to report crimes, then the observed relationship between crime rates and neighbourhood characteristics may become more difficult to interpret. In the future, it would be useful to include information collected in victimization and offender surveys (e.g., General Social Survey (GSS) on victimization). Such data sources may offer a wider scope and more information than what police-reported data may offer, since they include criminal incidents that may not be reported to the police and provide additional information on the individual characteristics of victims or offenders as well as on the incidents themselves, thus allowing for a more comprehensive investigation of crime phenomena.

Moreover, the police-reported crime data used in this study only include information on the major categories of offences, such as violence and property crimes, but exclude several crimes such as computer crimes (e.g., cyber terrorism, drug trafficking etc.), business crimes (e.g., fraud, money laundering etc.) that also warrant empirical investigation. Moreover, both violence and property crimes include several types of crimes that differ with respect to their spatial distributions. For example, a neighbourhood where break and enter incidents are frequently reported is not necessarily going to experience frequent reporting of theft incidents. However, both of these types of crimes are aggregated into the same broader category of property offence. Therefore, the examination of social contexts of crime just based on general crime categories (violent and property crimes) may potentially mask the unique social circumstances related to specific crime types. If more data on specific crime categories become available, future research into the spatial distribution of specific types of crime (e.g. assaults, thefts, robberies) and their relationships to social contextual characteristics would shed new light on the social mechanisms underlying crime distributions.

An additional area for data improvement would be the inclusion of alternative measures on social contextual properties that would allow for more reliable and valid explanation of their ecological impacts on crime rates. Due to data constraints, this study relied on census variables as indicators of neighbourhood conditions. Census data include useful demographic, economic, educational, and housing information for geographic areas, but they do not provide substantial information on the intermediary mechanisms that turn such neighbourhood contextual characteristics into neighbourhood effects. For example, census-based measures of socioeconomic characteristics of neighbourhoods (e.g., the percentage of low-income households) do not represent any mechanism that may explain why more disadvantaged neighbourhoods are associated with higher crime rates. In the future, it would be useful to seek for other data sources (e.g., city-administrative data) that allow for more direct measures of neighbourhood social processes or mechanisms, such as variables on social networks, collective efficacy, institutional resources, and community engagement that potentially counteract or buffer the impact of neighbourhood stressful conditions (e.g., poverty, residential instability and ethnic heterogeneity) on crime (Sampson and Groves, 1989; Sampson et al., 1997). Empirical research including such variables would offer better interpretative possibilities regarding the relationships between neighbourhood contexts and crime rates.

It will also be necessary to pursue our multilevel analyses in more depth, mainly in three ways. First, the aggregated data used in this study restricted our multilevel analysis to the neighbourhood and city levels while not taking individual-level factors into account. As widely documented by the literature, people make residential choices that depend on their personal characteristics (e.g. gender, age, marital status and ethnicity), as well as characteristics of the neighbourhood, and in turn, this selection process generates a compositional effect that is

independent of contextual effects in shaping neighbourhood-level outcomes (Kubrin and Weitzer, 2003). Thus, it is reasonable to assume that at least part of crime differences across neighbourhoods can be explained by the characteristics of individuals who live there. If these individual characteristics are related to crime, and are differentially distributed across neighbourhoods, they would offer a compositional explanation for neighbourhood-level differences in crime rates (Van Wilsem, 2003). In the future, greater efforts should be targeted towards the collection of individual-level data by a large scale survey across cities, which will provide opportunities to incorporate individual, neighbourhood and city characteristics into three-level multilevel models to simultaneously estimate their impacts on crime. As such, the hypotheses on the relationship between crime and social contexts (neighbourhood and city characteristics) could potentially be tested more optimally, as the potentially confounding influences of individual-level attributes have been taken into account.

Second, owing to the small number of cities ( $n=6$ ) with data available for our research, we were restricted to examining city contextual effects using only two city-level variables. It should also be noted that the power to estimate between-city variance and city-level effects is highly dependent on the number of cities included. Thus, the failure to observe significant city-level effects in this study should not simply be taken as an indication that city contexts can be ignored in the analysis, as the small number of cities has substantively reduced the power to detect significant effects at the city level and thus tends to underestimate the effects of city characteristics. Therefore, a direction for future research is to use a larger sample of cities and introduce additional measures of city characteristics, thus permitting a more thorough investigation of city contextual effects.

Third, although the study found strong spatial effects on neighbourhood crime rates, more research is required to learn more about the sources of spatial effects. As previously discussed, spatial effects can operate via two separate processes: (a) “diffusion” which describes a spatial process intrinsic to a given outcome, such that the outcome in a geographic area predicts an increased likelihood of similar outcomes in neighboring areas (Morenoff, 2003), and (b) spatial “exposure” to social processes underlying the outcome (i.e., measured or unmeasured independent variables), which spill over multiple geographic areas to exert overarching influences (Morenoff, 2003). In this study we obtained an overall estimate of spatial effects, however, we have yet to disentangle the relative contributions of diffusion and exposure processes. Future research may be conducted to distinguish between these two sources of spatial dependence, which would not only allow for a better specification of the spatial structure of our multilevel models, but lead to important substantive implications for crime research. From a crime prevention perspective, it would be particularly interesting to examine which contextual characteristics are more likely to span geographic boundaries to produce crime-related impacts. For example, if certain social processes (e.g., collective efficacy) are shown to exert protective effects on crimes not only in a local neighbourhood, but also in multiple proximate areas, then crime intervention strategies aimed towards promoting such social processes are more likely to achieve their objectives.

Finally, given that the findings presented here are based on cross-sectional data, it would be erroneous to conclude that the observed relationship between crime and social contexts is a direct causal link. In fact, the theoretical possibility that the relationship between crime and social context is a reciprocal one has been recognized in crime literature, as Van Wilsem (2003) stated, “crime may not only be an outcome of restrictive social circumstances, but also a cause of them”.

It has been argued that local crime can be a determinant of various types of behavior, such as moving house, fear, and lack of informal surveillance (Van Wilsem, 2003). Such behavior in turn, may cause more delinquency and crime to occur. The potential reciprocal relation between crime and social context has not received much attention in empirical studies. Therefore, future research into this issue is needed in conjunction with time-series data collection for neighbourhoods and cities. Examining crime and social contextual variables over a period of time would shed new light on the relationship between crime and social context, and perhaps lead to more conclusive empirical findings.

### **7.3. Conclusion**

This study contributes to the Canadian literature on criminology and urban social geography by exploring the spatial patterns of police-reported crime rates across select Canadian urban neighbourhoods and their relationships with both neighbourhood- and city-level characteristics, while adjusting for spatial dependence. More specifically, analyses were based on aggregated data at the census tract (dissemination area) level from the 2001 Incident-Based Uniform Crime Reporting Survey (UCR2) and the Census of Population for six Canadian cities: Edmonton, Halifax, Montreal, Saskatoon, Thunder Bay and Toronto. Exploratory spatial data analysis (ESDA) involved data visualization and spatial autocorrelation analysis to examine the spatial distributions of crime, as well to test for spatial dependence in the crime data. By applying multilevel modelling and spatial econometric techniques, neighbourhood violent and property crime rates were modelled respectively as a function of both city- and neighbourhood-level contextual variables, while controlling for spatial dependence.

The findings of this study have three main contributions, which may offer improvements over previous research. First, this study improves upon city-specific research by providing an inter-city comparison of the patterns and trends in the spatial distribution of crime in the Canadian context. A general trend can be observed that crime is not distributed randomly, but rather tends to be concentrated in particular neighbourhoods, notably around the city centers of these cities. This study also highlights the important regional variance in the Canadian urban system that the geography of crime varies significantly not only within cities, but also between cities. In larger cities, such as Toronto and Montreal, the spatial distribution of crime exhibited a more dispersed pattern with several crime hotspots scattered throughout the city rather than constrained to the city center or downtown areas. In contrast, relatively smaller cities, such as Thunder Bay, showed an exclusive concentration of the higher crime rates constrained to the city center. These findings suggest that larger spatial structures, such as the geography of a city may interact with neighbourhoods in shaping the spatial distributions of crime. This provides evidence for the notion that spatial organization of crime can be seen as a result, at a given moment in time, of the slow and complex process of urban development (Savoie, 2008b).

Second, within a multilevel framework, the study expands on previous neighbourhood crime research by considering not only local neighbourhood characteristics, but also the wider spatial context within which the neighborhood is embedded, and how both the local and broader social contexts are related to crime. The results indicate that local socioeconomic, demographic and dwelling characteristics of neighbourhoods account for a large amount of neighbourhood variance in crime rates; however, they are constrained by the wider social environment where neighbourhoods are embedded. Moreover, neighbourhoods are interdependent and crime rates in a given neighbourhood are related to the characteristics of surrounding neighbourhoods, possibly



due to a “diffusion” process where crime in a neighbourhood is likely to increase the likelihood of crime in nearby neighbourhoods, or and “exposure” process generated by social conditions that spill over neighbourhood boundaries to exert overarching crime-reducing or crime-inducing influences. On the other hand, city-level circumstances may have a hierarchical effect on neighbourhood crime rates as city characteristics may reflect the availability of local government resources to deter crime (e.g., the level of public social control exercised by police), as well as the general social climate (e.g., social, economic and population profiles) that acts with local neighbourhood conditions to shape the distribution of crime. In short, these findings suggest that the theoretical understanding and empirical estimation of social contextual effects on crime can be improved by including multiple social contexts instead of solely the neighbourhood and by taking spatial interdependency among neighbourhoods into account.

Finally, the findings of this study have important implications for the development and implementation of crime reduction strategies. First, these results indicate that strategies aimed at crime reduction or prevention should be developed in light of specific local socioeconomic, demographic and landuse conditions as they can vary across an urban area and affect the success of crime intervention efforts. Second, and equally importantly, neighbourhood intervention efforts should not neglect pressures toward crime from forces external to the immediate neighbourhood in the wider social environment. This study suggests that it is inappropriate to abstract the neighbourhood from its wider spatial context and public policy for crime reduction should treat neighbourhoods as spatially interdependent parts of a broader social environment.

In short, the findings of both local and wider social environmental influences on neighbourhood crime suggest that crime policy and intervention efforts that deal with the specific needs of each

city and the resources available at neighbourhood levels are more likely to achieve desired objectives and for supporting crime prevention efforts.

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## Appendix A

**Table A.1** – Descriptive statistics for the dependent variable and independent variables

	<b>Minimum</b>	<b>Maximum</b>	<b>Mean</b>	<b>Std. Deviation</b>
<b>Dependent Variables (N=1479)</b>				
Violent crime rate	184.70	9.25	9.64	184.70
Property crime rate	550.63	36.47	33.27	550.63
<b>Neighbourhood-level Independent Variables (N=1479)</b>				
Index of Concentration at the Extremes (ICE)	-0.88	0.87	0.00	0.26
Percentage of Aboriginal population	0.00	54.70	2.43	5.26
Percentage of dwellings built before 1961	0.00	104.00	37.97	31.48
Percentage of dwellings that require major repairs	0.00	66.70	7.78	4.96
Percentage of lone-parent families	0.00	64.30	18.14	8.70
Percentage of multifamily household	0.00	18.10	2.10	2.72
Percentage of owner-occupied household	0.00	104.00	51.17	26.46
Percentage of people who are single	10.10	76.50	38.41	11.93
Percentage of young males	0.00	20.70	6.85	2.03
Percentage of population aged 65 years and over	0.00	87.40	13.88	7.90
Percentage of recent immigrants	0.00	59.70	11.00	10.76
Percentage of residents in low-income households	0.00	79.60	18.72	12.96
Percentage of residents without high school diploma	0.00	70.90	25.02	12.00
Percentage of visible minorities	0.00	95.60	23.32	21.35
Population Density	48.29	70543.48	6149.38	5348.16
Residential Stability	1.10	86.70	52.59	12.77
Unemployment rate	0.00	47.40	7.75	4.13
<b>City-level Independent Variables (N=6)</b>				
Population	109000.00	2503281.00	913238.83	1007902.49
Population per Police Officer	452.00	664.00	543.50	74.14

**Table A.2** – Pearson’s correlation coefficients between neighbourhood-level independent variables

	<b>V1</b>	<b>V2</b>	<b>V3</b>	<b>V4</b>	<b>V5</b>	<b>V6</b>	<b>V7</b>	<b>V8</b>	<b>V9</b>	<b>V10</b>	<b>V11</b>	<b>V12</b>	<b>V13</b>	<b>V14</b>	<b>V15</b>	<b>V16</b>	<b>V17</b>
<b>V1</b>	1	-.090**	-.182**	-.176**	-.307**	-.155**	.627**	-.267**	-.117**	.073**	-.383**	-.041	-.619**	-.379**	-.363**	.401**	-.588**
<b>V2</b>	-.090**	1	-.092**	.048	.205**	-.061*	.096**	-.007	.209**	-.113**	-.294**	.134**	.123**	-.289**	-.178**	-.152**	.107**
<b>V3</b>	-.182**	-.092**	1	.575**	.275**	.056*	-.196**	.473**	.015	.049	.145**	-.042	.035	.116**	.102**	-.134**	.181**
<b>V4</b>	-.176**	.048	.575**	1	.353**	.044	-.174**	.393**	.039	-.012	.115**	.014	.043	.095**	.036	-.152**	.189**
<b>V5</b>	-.307**	.205**	.275**	.353**	1	-.014	-.256**	.453**	.064*	-.013	-.046	.086**	.184**	-.044	.063*	-.189**	.281**
<b>V6</b>	-.155**	-.061*	.056*	.044	-.014	1	.253**	-.169**	.062*	-.152**	.473**	-.155**	.290**	.633**	-.041	.206**	-.026
<b>V7</b>	.627**	.096**	-.196**	-.174**	-.256**	.253**	1	-.423**	.011	-.097**	-.287**	-.140**	-.212**	-.150**	-.553**	.657**	-.507**
<b>V8</b>	-.267**	-.007	.473**	.393**	.453**	-.169**	-.423**	1	.264**	-.097**	-.022	-.030	-.070**	-.094**	.226**	-.405**	.283**
<b>V9</b>	-.117**	.209**	.015	.039	.064*	.062*	.011	.264**	1	-.473**	-.028	-.047	-.127**	.032	-.086**	-.217**	.131**
<b>V10</b>	.073**	-.113**	.049	-.012	-.013	-.152**	-.097**	-.097**	-.473**	1	-.090**	.103**	.212**	-.137**	-.029	.181**	-.041
<b>V11</b>	-.383**	-.294**	.145**	.115**	-.046	.473**	-.287**	-.022	-.028	-.090**	1	-.099**	.106**	.872**	.396**	-.170**	.281**
<b>V12</b>	-.041	.134**	-.042	.014	.086**	-.155**	-.140**	-.030	-.047	.103**	-.099**	1	.029	-.114**	.015	-.065*	.125**
<b>V13</b>	-.619**	.123**	.035	.043	.184**	.290**	-.212**	-.070**	-.127**	.212**	.106**	.029	1	.207**	.053*	.072**	.340**
<b>V14</b>	-.379**	-.289**	.116**	.095**	-.044	.633**	-.150**	-.094**	.032	-.137**	.872**	-.114**	.207**	1	.251**	-.057*	.246**
<b>V15</b>	-.363**	-.178**	.102**	.036	.063*	-.041	-.553**	.226**	-.086**	-.029	.396**	.015	.053*	.251**	1	-.351**	.329**
<b>V16</b>	.401**	-.152**	-.134**	-.152**	-.189**	.206**	.657**	-.405**	-.217**	.181**	-.170**	-.065*	.072**	-.057*	-.351**	1	-.326**
<b>V17</b>	-.588**	.107**	.181**	.189**	.281**	-.026	-.507**	.283**	.131**	-.041	.281**	.125**	.340**	.246**	.329**	-.326**	1

Note: \* correlation is significant at the 0.01 level (2-tailed)

\*\*correlation is significant at the 0.05 level (2-tailed)

- V1 = Index of Concentration at the Extremes (ICE)
- V2 = Percentage of Aboriginal population
- V3 = Percentage of dwellings built before 1961
- V4 = Percentage of dwellings that require major repairs

- V5 = Percentage of lone-parent families
- V6 = Percentage of multifamily household
- V7 = Percentage of owner-occupied household
- V8 = Percentage of people who are single
- V9 = Percentage of young males
- V10 = Percentage of population aged 65 years and over
- V11 = Percentage of recent immigrants
- V12 = Percentage of residents in low-income households
- V13 = Percentage of residents without high school diploma
- V14 = Percentage of visible minorities
- V15 = Population Density
- V16 = Residential Stability
- V17 = Unemployment rate

**Table A.3 – Equations for hierarchical linear models used in this study**

<b>Model</b>	<b>Level 1 model</b>	<b>Level 2 model</b>	<b>Combined model</b>
Model 1: One-way random-effect ANOVA with random effects	$Y_{ij} = \beta_{0j} + \varepsilon_{ij}$	$\beta_{0j} = \gamma_{00} + \delta_{0j}$	$Y_{ij} = \gamma_{00} + \delta_{0j} + \varepsilon_{ij}$
Model 2: One-way random-effect ANCOVA model	$Y_{ij} = \beta_{0j} + \sum_{p=1}^P \beta_{pj}(X_{pij} - \bar{X}_{p.j}) + \varepsilon_{ij}$	$\beta_{0j} = \gamma_{00} + \delta_{0j}$	$Y_{ij} = \gamma_{00} + \sum_{p=1}^P \beta_{pj}(X_{pij} - \bar{X}_{p.j}) + \varepsilon_{ij} + \delta_{0j}$
Model 3: Spatial hierarchical linear model	$Y_{ij} = \beta_{0j} + \sum_{p=1}^P \beta_{pj}(X_{pij} - \bar{X}_{p.j}) + \rho W y + \varepsilon_{ij}$	$\beta_{0j} = \gamma_{00} + \delta_{0j}$	$Y_{ij} = \gamma_{00} + \sum_{p=1}^P \beta_{pj}(X_{pij} - \bar{X}_{p.j}) + \rho W y + \varepsilon_{ij} + \delta_{0j}$
Model 4: Full random-intercept model	$Y_{ij} = \beta_{0j} + \sum_{p=1}^P \beta_{pj}(X_{pij} - \bar{X}_{p..}) + \rho W y + \varepsilon_{ij}$	$\beta_{0j} = \gamma_{00} + \sum_{q=1}^Q \gamma_{0q} Z_{qj} + \delta_{0j}$	$Y_{ij} = \gamma_{00} + \sum_{p=1}^P \beta_{pj}(X_{pij} - \bar{X}_{p..}) + \sum_{q=1}^Q \gamma_{0q} Z_{qj} + \rho W y + \varepsilon_{ij} + \delta_{0j}$

Note:

- $Y_{ij}$  is the violent/property crime rate for neighbourhood  $i$  in city  $j$ ;
- $X_{pij}$  is the value of neighbourhood-level variable  $X_p$  for neighbourhood  $i$  in city  $j$ ;
- $\bar{X}_{p.j}$  is the mean of neighbourhood-level variable  $X_p$  for neighbourhoods in city  $j$  (group-mean);
- $\bar{X}_{p..}$  is the overall mean of neighbourhood-level variable  $X_p$  (grand-mean);
- $\beta_{0j}$  is the city-specific intercept, the mean value of neighbourhood crime rates in city  $j$ ;
- $\beta_p$  is the regression coefficient of neighbourhood-level variable  $X_p$  ( the main effect of  $X_p$  which is fixed or constant across all the cities);
- $\varepsilon_{ij}$  is the neighbourhood-level random effect that represents the deviation of neighbourhood  $i$ 's outcome from the predicted outcome based on the values of  $X_p$ ; this residual is assumed to be independent and normally distributed within each city, with a mean of 0 and a variance of  $\sigma^2$ ;
- $\gamma_{00}$  is the overall intercept;
- $\gamma_{0q}$  is the main effect of  $Z_q$  (averaged over all cities in the population);
- $\delta_{0j}$  is a city-level random effect that represents the unique deviation of the intercept of city  $j$  from the overall intercept  $\gamma_{00}$  after accounting for the effect of  $Z_q$ ; it is the city-level residual assumed to be independent from the neighbourhood-level residuals  $\varepsilon_{ij}$  and have a normal distribution with mean 0 and a variance of  $\tau_{00}$ .