Risky Places and Criminogenic Facilities: Understanding Property Crime at Micro-Spatial Units

by

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Abstract

Criminologists have long-known that spatial crime patterns vary across different geographic areas. Until recently, research has shown that crime is highly concentrated at a small number of micro-places. Subsequent studies have found that these spatial patterns are generalizable across different urban settings and are relatively stable over time. Although more scholars are beginning to recognize the importance of measuring crime at places, little is known about the explanatory factors of crime at the micro-spatial scale. Using police incident data and land-use information obtain from the Vancouver Open-Data catalogue, zero-inflated negative binomial models were used to understand the spatial patterns of various types of property crimes at street segments. The results demonstrate that certain facilities have a significant impact on these crime types at the micro-spatial level. Depending on the crime type, the strength of the relationship varies in magnitude and level of significance.

Keywords: crime and place; street segments; property crime; count data; theory integration; zero-inflated negative binomial
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Chapter 1.

Introduction

Theoretical explanations of crime and deviance have traditionally been applied at the individual level. For instance, dating back to the seventeenth century, early theories of deviancy and criminal behaviour were strongly influenced by religious belief and demonological phenomena (Vold, 1958, p. 5). During the rise of scientific reasoning and the Age of Enlightenment, these supernatural explanations of crime and delinquency were eventually replaced by the classical and positivist school of criminology (Beccaria, 1775/2009; Bentham, 1789/1960; Lombroso, 1876/2006). Instead of being possessed by demonic forces, scholars argued that individuals actually exhibit rational choice and free will (Beccaria, 1775/2009; Bentham, 1789/1960). Because of these early theories in criminology, empirical research has mainly focused on investigating the social, psychological and biological factors that affect criminal behaviour of the individual. In a historical sense, criminologists have overlooked the importance of studying the spatial distributions and temporal patterns of criminal activity (Andresen, 2010).

Although spatial criminology is now well-recognized as a discipline, investigations of the spatial-temporal elements of crime did not become commonplace until the establishment of the Chicago School of Sociology (Burgess, 1925; Park, 1915; Shaw & McKay, 1942, 1969) and the development of environmental criminology (Brantingham & Brantingham, 1981, 1995; Clark & Cornish, 1987; Cohen & Felson, 1979; Jeffery, 1971). Moreover, scholars who belong to the former group are mainly focused on measuring the effects of structural characteristics on criminal activity and victimization (Sampson & Groves, 1989; Shaw & McKay, 1942). On the other hand, scholars who conduct research in the former group are more concerned about how the geographic landscape impacts criminal behaviour.

In historical terms, spatial analyses have been conducted at meso-level units (i.e. census tracts, census group blocks and neighbourhoods) and applied sociological constructs to explain social disorder and crime. Today, contemporary research in spatial criminology is shifting analyses to micro-spatial units (i.e. street segments, street block groups, or discrete addresses) to explain different patterns of crime. This division of
research is commonly referred to as the crime and place literature. Furthermore, scholars have determined that crime is highly concentrated at a small number of places (Sherman, Gartin & Buerger, 1989; Weisburd, Bushway, Lum & Yang, 2004;) and these concentrations are relatively stable over time (Andresen, Linning, & Malleson, 2017; Braga, Hureau & Papachristos, 2011; Haberman, Sorg & Ratcliffe, 2017).

Although these patterns of concentration were discovered across different study settings, very few researchers have applied these spatial crime theories at micro-places. Smith, Frazee and Davison (2000) were the one of the first to integrate social disorganization and routine activity theory at micro-spatial units. Furthermore, they developed interaction effects using constructs from these two theories and incorporated these variables into the final statistical model. Using street segments as the unit of analysis (originally referred to as face blocks), they found that many of their predictors and interaction effects had a significant impact on robberies within the study setting. Almost a decade later, another group of scholars attempted to apply social disorganization and routine activity theory to explain the concentrations of crime at street segments (Weisburd, Groff & Yang, 2012). Similar to the previous study, Weisburd and colleagues (2012) were successful at operationalizing constructs from both theories and discovered that several of their predictors significantly impacted these crime concentrations.

As mentioned previously, there is limited research that investigates the causal factors of these concentrations of crime at micro-places. By the incorporating prominent theories in spatial criminology and using the previous studies as an empirical framework, the intention of this thesis is to contribute to the crime and place literature. More specifically, this study will conduct a preliminary investigation into the explanatory factors of different types of property crime at street segments within Vancouver.
Chapter 2.

Theoretical and Historical Developments of Crime and Place

The development of crime and place has emerged from a series of waves within the academic literature. The first wave of studies stems from research in the nineteenth century from statisticians from Western European countries (Glyde, 1856, Guerry, 1833; Quetelet, 1842). These studies were monumental to developing the spatial criminological literature because these researchers were able to identify that crime rates were patterned across variation levels of levels of aggregations – countries, provinces, counties, cities, towns and wards. Furthermore, areas with high crime rates and known offender residences had positive connection to other social problems and disorders, such illiteracy, poverty and high population density. Based off these findings from the research, scholars were beginning to recognize that crime and delinquency had some empirical connection to space and place.

The second wave of spatial research was developed by American scholars in the early twentieth century, primarily from the Chicago School of Sociology. Researchers from this school were interested in understanding how the urban form and urban development had an impact on the spatial patterns of crime (Burgess, 1916; Burgess, 1925; Park et al., 1925). As one of the consequences of a growing city, people were constantly in competition for limited social and spatial resources (Burgess et al., 1925). Because of this competition, areas adjacent to the city centre were run-down with abandoned buildings, limited social services and undesirable living conditions – i.e. the zone-in-transition (Burgess, 1925). Consequently, crime and delinquency were more conducive to these areas with high levels social disorganization – i.e. economic deprivation and social disorder (Shaw & McKay, 1942).

Although the previous waves of research have given focus to the spatial aspect of crime, the importance of place and crime has been overlooked by mainstream criminology. The third wave emerged from a group of researchers across three different countries throughout western world in the late twentieth century. These scholars were interested in understanding criminal activity through an opportunity perspective (Clarke & Cornish,
1987; Cohen & Felson, 1979) and understanding how the geographic landscape affected criminal behaviour (Brantingham & Brantingham, 1993, 1995; Jeffery, 1971). Because of shifting trends in criminology and partly from criticisms of the social disorganization perspective, these researchers were concerned about the specific interactions between offenders and targets at specific places. Instead of focusing on neighbourhood covariates that might have an impact on crime at the meso-level, opportunity models of crime place emphasis on the micro-level interactions that cause an offender and a target to come together within time and space (Cohen & Felson, 1979). Until the development of environmental criminology and opportunity crime theories, the spatial components of crime were not taken seriously as a discipline in order to understand the crime problem.

The final wave of spatial research that established the discipline of crime and place emerged from several studies that were conducted in the late twentieth and early twenty-first century. Sherman and colleagues (1989) were the first group of scholars to consider micro-places as a viable unit of analysis. Using discrete address locations, they found that a surprisingly small number of places accounted for a large amount of calls for service to the police in Minneapolis, Minnesota (Sherman et al., 1989). More specifically, approximately three percent of places generated fifty percent of the calls for service. The second most notable crime and place study was completed by Weisburd and colleagues (2004) in Seattle, Washington. Interestingly, these scholars found similar patterns of crime concentration at micro-places over fourteen-year period and demonstrated remarkable stable patterns over time (Weisburd et al., 2004). These two studies were fundamentally important for establishing a solid foundation for this novel and emerging field of crime and place research. Furthermore, subsequent research studies have been able replicate similar patterns of concentration at different geographic settings and different time periods (Andresen et al., 2017; Bernasco & Block, 2011; Braga et al., 2011; Curman et al., 2015; Gill et al., 2017; Haberman et al., 2017; Schnell et al., 2017). In addition, other scholars are attempting to uncover the explanatory factors that cause crime to concentrate at such a small number of locations (Smith et al., 2000; Weisburd et al., 2012). However, there are only a small number of studies that have investigated this phenomenon because the type of data needed for these research studies are not often readily available.
2.1. Early Research in Spatial Criminology

Prior to these developments in spatial criminology within the twentieth century, there are several notable studies that utilized geographic statistics in order to analyze criminal activity. Guerry (1833) and Quetelet (1842) are some of earliest known researchers to adopt a theoretical framework that incorporated geographic analysis to determine that crime is not "homogeneously distributed across" space (as cited in Brantingham & Brantingham, 1981a, p. 10). By analyzing official crime statistics from French departments, Quetelet (1842) discovered that property crimes were prevalent in urbanized settings and violent crimes were concentrated in rural areas. During this same period, Glyde (1856) conducted similar research in England by analyzing the spatial distribution of crime among the different towns in Suffolk County. Glyde (1856) concluded that criminal activity was spatially heterogeneous. Furthermore, Burgess (1916) examined the spatial patterns of juvenile delinquency in a rural American town and discovered that certain districts had a disproportionately high number of court referrals. Although these studies were instructive and highlighted the importance of spatial analysis, it is difficult to generalize these results because the sample sizes were too small, and units of analysis were too large. Moreover, the spatial aspect of crime did not receive significant recognition until the Chicago School of Sociology became an influential institution.

In the early twentieth century, American towns were experiencing drastic and significant changes in response to the Industrial Revolution; rural and agrarian communities were rapidly becoming urban and industrialized metropolitan areas (Shaw & McKay, 1942). For instance, Chicago was a prime example of an American city to experience this explosive growth; the population grew from two-hundred people to a population of over three million in just over a century (Shaw & McKay, 1942). Consequently, scholars established the Chicago School of Sociology in order to describe and explain the social ecology and urban growth patterns within the modern city (Burgess, 1925; Park, 1915). Earnest W. Burgess (1925) iterated that patterns of urban growth could easily be illustrated "by a series of concentric circles" (p. 50). This concentric zone model, therefore, demonstrates that urban growth is concentrated in the central business district and expands outwards to the surrounding areas (Burgess, 1925). As the central district rapidly expands and spatial resources become scarce, industrial factories and commercial businesses will encroach upon the adjacent residential neighbourhoods (Burgess, 1925).
Consequently, the living conditions of these neighbourhoods were unattractive and undesirable because these areas were constantly under transition – often referred to as the zone in transition (Burgess, 1925). In time, these developments in social ecology would influence Shaw and McKay (1942) to develop social disorganization theory.

2.2. Social Disorganization Perspective

Social disorganization theory originally emerged from social ecological and ethnographic research from the Chicago School of Sociology in the early twentieth century. During this time, Shaw and McKay (1942) developed a theoretical model to explain crime and delinquency at the neighbourhood level. They argued that neighbourhood characteristics such as economic deprivation, population turnover and ethnic heterogeneity would lead to higher levels of criminal activity (Shaw & McKay, 1942). As the century progressed, scholars were beginning to criticize macro-level theories of crime, and criminological research was trending towards opportunity perspectives and social learning theories of crime (Bursik, 1988, p. 523). It was not until the late twentieth century where researchers attempted to revitalize the social disorganization perspective by developing a model that was more appropriate for contemporary crime research and incorporated a systemic approach to communities and crime (Bursik & Grasmick, 1993; Sampson & Groves, 1989; Sampson, Raudenbush, Earls, 1997).

2.2.1. Social Disorganization Theory – Original Model

The social disorganization model is perhaps one of the most influential theories in spatial criminology. Instead of examining the characteristics of individual offenders, social disorganization theory is concerned about the sociological causes of criminal behaviour and delinquency at the neighbourhood level (Shaw & McKay, 1942). By incorporating the principles of social ecology and the concentric zone model, Shaw and McKay (1942) argued that certain neighbourhood structures would significantly increase the levels of criminal activity. Using juvenile court records, Shaw and McKay (1942) identified the different areas on a map of Chicago that had reoccurring problems of juvenile delinquency and criminal activity. According to their central proposition, there are three structural covariates that significantly affect criminal activity and juvenile delinquency: ethnic heterogeneity, population turnover and socioeconomic status (Shaw & McKay, 1942).
After completing their analyses, Shaw and McKay (1942) discovered that neighbourhoods with high levels of ethnic diversity also had higher crime rates in comparison to ethnically homogenous neighbourhoods. This is because recent immigrants at this time could only afford to live in the transitional neighbourhoods adjacent to the city centre (Shaw & McKay, 1969). Because residents within these neighbourhoods were primarily immigrants from different countries with diverse culturally backgrounds, it was difficult for these families to communicate with each other (Shaw & McKay, 1969). Consequently, ethnic heterogeneity did not have a direct effect on crime, but rather it was the cultural diversity and language barriers that impeded the development of community organization and collective social control (Shaw & McKay, 1969). Thus, the criminal justice system would become responsible for controlling and punishing delinquent behaviour, and therefore increase the official crimes rate for these neighbourhood.

The other structural characteristic that was expected to have a significant impact on crime is the rate of population turnover within a neighbourhood (Shaw & McKay, 1942). Shaw and McKay (1969) found that delinquency rates were higher in neighbourhoods that had a decreasing residential population, in comparison to neighbourhoods with an increasing residential population (p. 91). Notably, these neighbourhoods with high rates of population turnover were located in the transition zone (Shaw & McKay, 1969). These scholars further argued that population change in a neighbourhood does not compel “a boy to become a delinquent,” but instead a decreasing population is a result of industrial invasion, which contributes to an environment that promotes delinquent behaviour (Shaw & McKay, 1969, p. 92). In other words, the relationship between population turnover and crime is indirect and non-linear. For example, these residents did not attempt to participate in any community organizations because families were trying to move out of these neighbourhoods as quickly as possible because of the poor living conditions. With this mentality, it would not be reasonable to establish social ties to the community or attempt to improve the social conditions of the neighbourhood.

Another contributing factor that affected neighbourhood residential stability was the percentage of home ownership. From their analyses, Shaw and McKay (1969) were able to determine that neighbourhoods with a high percentage of home ownership had lower rates of delinquency, which were often located in the suburban areas of Chicago. In contrast, neighbourhoods with low percentage of home ownership had higher rates of delinquency, which were located in the transition areas (Shaw & McKay, 1969). By
interpreting these results, the assumption is that families that own their homes are expected to reside in a neighbourhood for a longer period of time. Consequently, residents of these neighbourhoods are more likely to develop social connection with fellow residents and participate in community organizations. The opposite would be true for neighbourhoods in the transition zone with more low-cost rental housing units. Population turnover, therefore, has an indirect relationship with criminal activity because of a neighbourhood’s ability or inability to informally control delinquent behaviour.

Lastly, socioeconomic status (SES) was the final neighbourhood covariate that Shaw and McKay (1942) considered to have an impact on crime and delinquency. Using levels of social assistance, poverty and median rental prices as an indicator of SES, these researchers found that neighbourhoods with lower SES had higher rates of delinquency (Shaw & McKay, 1969). Again, these areas with lower SES were concentrated in the neighbourhoods adjacent to the city centre. Although areas with low SES had higher rates of crime, there was not a direct relationship between these to concepts. To further elaborate, it is harder for residents to mobilize necessary resources to control delinquent behaviour because of the prevalence of social disorganization in poor neighbourhoods (Shaw & McKay, 1969). Because of this indirect relationship, growing up in poverty made it difficult for juveniles to rise above the ranks within the social hierarchy of the conventional system because of the limited opportunities for employment training and education (Shaw & McKay, 1969, p. 116). As a result, “a career in delinquency and crime” becomes the only option for economic gains and escaping the life of extreme poverty (Shaw & McKay, 1969, p. 115). Consequently, it is easier for the criminal milieu to manifest in neighbourhoods that have low economic prospects and very few measures of social control.

To conclude, social disorganization theory predicts that neighbourhoods with the following characteristics are too disorganized to collectively control the activities of juvenile delinquents (Shaw & McKay, 1942). Thus, social disorganization is defined as a lack of social cohesion that inhibits local residents to implement effective crime prevention measures (Andresen, 2010, p.11). Because these neighbourhoods are unable to implement informal measures of social control and lack social cohesion, the criminal justice system takes responsibility to punish and deter crime and delinquency through formal control measures.
Criticisms

Although Shaw and McKay’s social disorganization theory is highly influential and has been widely cited in subsequent ecological studies, scholars have criticized the ability of this model to provide direct causal explanations of crime (Bursik, 1988, p. 519; Bursik & Grasmick, 1993). For instance, the model proposes that structural covariates have an indirect effect on crime and is mediated through social cohesion (Shaw & McKay, 1969). Consequently, social cohesion has a causal effect on crime, not the structural covariates (Andresen, 2010, p.13). The association is between “social cohesion… and crime often is referred to as [a] reduced-form relationship” (Andresen, 2010, p.13). As a result, testing social disorganization theory with reduced-form relationships will produce results that are potentially circumstantial (Andresen, 2010, p.13). Therefore, studies must include “variable[s] that intervene between community structures and delinquency” in order to avoid this problem and directly test this theory (Sampson & Groves, 1989, p.775). Sampson and Groves (1989) argued that official census data rarely provides information on social cohesion. Heitgerd and Bursik (1987) also asserted that early ecological studies were unable to examine the internal processes and formal social networks of the community.

In terms of other criticisms, the assumption of the original social disorganization model is that structural characteristics and ecological dynamics are stable over time (Bursik, 1986, p. 35). On the contrary, “the resident[ial] population of any community will change considerably over time” due to the variation in birth rates, death rates and migration patterns (Reiss, 1986, p. 29). Ecological studies that analyze the spatial distribution of crime, therefore, must take into consideration that neighbourhood structures are constantly changing (Burisk & Webb, 1982, p. 27). Consequently, recent developments in structural processes can only be detected by analyzing longitudinal data (Burisk, 1984; Bursik, 1988, p.525). These structural changes suggest that the relationship between crime and economic deprivation is rather different from what Shaw and McKay had originally envisioned (Bursik & Grasmick, 1993). This example demonstrates that the contextual aspects of society must be taken into consideration before applying the social disorganization model to explain criminal activity. Because of the criticisms of social disorganization theory and the shifting trends in criminology, spatial crime research shifted towards the criminal opportunity model (Bursik, 1988, p. 523).
2.2.2. Social Disorganization Theory – Contemporary Model

To address this issue, Sampson and Groves (1989) revitalized the original social disorganization model by analyzing data from the British Crime Survey. Because this survey provided data on friendship networks and recreational participation, these researchers were able to construct intervening variables (Sampson & Groves, 1989). Furthermore, these intervening variables will affect the degree to which communities experience social disorganization. The first variable measures the ability to “supervise and control teenage peer groups” (Sampson & Groves, 1989, p. 778). In theory, neighbourhoods with low levels of social cohesion are unable to control delinquent behaviour through informal measures. Secondly, examining “local friendship networks” would be another measurement of community organization (Sampson & Grooves, 1989, p. 779). The expectation is that highly dense social networks will increase the levels of guardianship throughout a community (i.e. the ability to recognize strangers and prevent predatory victimization) and strong relational connections will discourage others from engaging in delinquent behaviour (Sampson & Groves, 1989, p. 779). Lastly, “local participation in formal and voluntary organizations” would measure the levels of social cohesion (Sampson & Groves, 1989, p. 779). If organizational ties are weak within a community, the youth population will become unattached and are less likely to be controlled. Furthermore, when institutions within the community are unstable and isolated, social cohesion becomes weak and social control is limited (Sampson & Groves, 1989). Through the contemporary social disorganization model, these intervening variables will have a mediating effect between community structures and crime.

Furthermore, the contemporary model of social disorganization included two additional structural variables: family disruption and urbanization (Sampson & Groves, 1989). Because previous research had shown that these variables had a significant effect on victimization (Sampson, 1983, Sampson, 1987), these researchers decided that it would be important to include this predictor into the model (Sampson & Groves, 1989). Communities are complex systems of social networks and relationships that greatly influence the socialization process. Considering that social processes and dynamic structural characteristics, Sampson and Groves (1989) argued that a systemic model is more appropriate. The assumption of the original and contemporary social disorganization model is that “structural barriers [will] impede [the] development of formal and informal
ties" that enable a community to become self regulated (Sampson & Groves, 1989, p. 777).

After conducting their analyses, Sampson and Groves (1989) were able to determine that several intervening variables had a significant impact on different types of crime and the strength of the relationship varied. Most notably, unsupervised peer teenage groups had the largest positive effect on violent victimization and local friendship networks had a negative effect on violent crime. With respect to property offenses, these scholars found that burglary rates were much lower in communities that were able to control teenage groups effectively, had extensive friendship networks and high organizational participation (Sampson & Groves, 1989). Interestingly, socioeconomic status appeared to have a non-significant effect on all three violent crime categories when incorporating intervening variables into the analyses (Sampson & Groves, 1989). Without testing these intervening variables, Sampson and Groves (1989) argued that the relationship between neighbourhood structures and crime is circumstantial.

To further contribute to the contemporary model of social disorganization, Bursik and Grasmick (1993) further discussed the limitations of the original theoretical perspective. Similar to Sampson and Groves (1989), these researchers asserted that the relationship between economic deprivation and crime is mediated by other factors (Bursik & Grasmick, 1993). More specifically, Bursik and Gramick (1993) emphasized that the original model failed "to consider the relational networks that pertain to [the] public sphere of control" (Bursik & Grasmick, 1993, p. 279). Considering these arguments, the relationship between neighbourhood structures and crime would therefore be mediated by a neighbourhood’s ability “to solicit human and economic resources from” public institutions (Bursik & Grasmick, 1993, p. 279).

Although both groups of researchers had similar criticisms of the original model, Bursik and Grasmick (1993) further addressed some issues with Sampson and Groves’ (1989) attempt to revitalize the social disorganization perspective. They argued that the Sampson and Groves’ (1993) study was not able to analyze “the effects of a changing urban economy” because they did not incorporate temporal components that would affect neighbourhood structures over time (Bursik & Grasmick, 1993, p. 270). When conducting their analyses, Bursik and Grasmick (1993) operationalized the constructs of social disorganization from census information and juvenile delinquency records from 1960 to
1980. Furthermore, these researchers needed to create variables that represented “the regulatory element of the social disorganization model” (Bursik & Grasmick, 1993, p. 271). Because they did not have access to data that directly measured relational networks and informal social control mechanism, they had to make indirect inferences from census data. Consequently, Bursik and Grasmick (1993) used percentage of owner occupancy, residential mobility, net migration levels and two-parent households as indictors social control and regulatory capacities (p. 272). After completing the analyses, they concluded that other social factors were having an impact on crime and delinquency that were not included in the original model or social disorganization (Bursik & Grasmick, 1993). The authors, therefore, proposed that a systemic model of social disorganization that accounts for private, parochial and public control mechanisms is more appropriate for contemporary communities and crime research (Bursik & Grasmick, 1993, p. 280).

Scholars within the realm of communities and crime were beginning to focus their research on how social cohesion within a community and the willingness of residents to intervene had an impact on violent and criminal activity. Sampson and colleagues (1997) would later define this concept as ‘collective efficacy’ and hypothesized that this concept would have negative effect on violence within a community. Using community surveys and multilevel analyses, these researchers found that neighbourhoods in Chicago with high-levels of collective efficacy had reduced levels of violence (Sampson, et al., 1997). In subsequent research into this concept, Sampson, Morenoff and Earls (1999) examined the spatial effects of structural covariates on collective efficacy for children in Chicago neighbourhoods. The results demonstrated that spatial proximity to “intergenerational closure, reciprocal local exchange, and shared expectations for information social control” has a greater effect of cultivating collective efficacy than structural characteristics (Sampson et al., 1999, p. 633). Lastly, Morenoff, Sampson and Raudenbush (2001) found that friendship networks, voluntary association and local organization promoted social cohesion. Neighbourhoods with high collective efficacy, therefore, had lower rates of homicide than neighbourhoods with concentrated disadvantage and low collective efficacy (Morenoff et al., 2001).

Although there had been numerous studies on communities and crime within a contemporary context, there had been limited efforts to directly test the contemporary social disorganization model. Consequently, it would be ideal that subsequent research replicate the work of Sampson and Groves (Lowenkamp et al., 2003, p. 352). There are,
however, very few “existing macro-level data sets” that contain similar intervening and structural measures of social control; therefore, a precise replication study had not been conducted (Lowenkamp et al., 2003, p. 352). To resolve these issues, Lowenkamp and colleagues (2003) analyzed data from the 1994 British Crime Survey and used the same variables specified in the original study.

As part of their analyses, Lowenkamp and colleagues (2003) examined the relationship between the structural covariates and intervening variables. These researchers found that local friendship networks had a significant and negative effect on ethnic heterogeneity, socioeconomic status and urbanization. On the other hand, these friendship networks had positive effect on residential stability, whereas family disruption had no relationship. Regarding unsupervised teenage peer groups, family disruption, urbanization and ethnic heterogeneity had a positive and significant relationship. The effects of residential stability were insignificant, while socioeconomic status had an inverse and significant relationship with teenage peer groups. Lastly, organizational participation was not as strong as the previous two intervening variables had a significant effect on residential stability, family disruption and ethnic heterogeneity (Lowenkamp et al., 2003, p. 360).

In addition to examining the relationship between neighbourhood characteristics and the intervening variables, Lowenkamp and colleagues (2003) analyzed these variables with victimization (p. 361). As theoretically expected, all three intervening variables of social disorganization had a significant effect on victimization. More specifically, unsupervised peer groups demonstrated to have a remarkably strong effect on victimization (Lowenkamp et al., 2003, p. 361). Moreover, these researchers sought out to determine if the intervening variables of social disorganization had a mediating effect on the structural characteristics (Lowenkamp et al., 2003, p. 361). When controlling for the intervening variables, residential mobility and family disruption did have a significant relationship with total victimization; however, ethnic heterogeneity, urbanization and socioeconomic status were not significant (Lowenkamp et al., 2003, p. 361). Overall, the Lowenkamp and colleagues’ study produced findings that were almost identical to the original study conducted by Sampson and Groves (1989). In fact, the results "generated from the more recent sample" demonstrated even more support for the social disorganization perspective than the previous study (Lowenkamp et al., 2003, p. 364).
These results, therefore, have strengthened the credibility of social disorganization theory to explain crime and social disorder within the contemporary urban setting.

2.3. Criminal Opportunity Perspective

The development of opportunity theories of crime was due to the shifting trends in criminology and partly because of the criticism of social disorganization theory. However, it is important to note that this paradigm shift within spatial criminology occurred before scholars were revitalized the social disorganization model. In the beginning of the 1970s, C.R. Jeffery (1971) published his influential book *Crime Prevention through Environmental Design* (CPTED) that would eventually establish the groundwork for environmental criminology. Adopting the principles of rational choice and deterrence from the classical school of criminology, Jeffery (1971) argued that crimes can be prevented by altering designs within the urban environment. According to this school of thought, the environmental conditions have an immediate and direct impact on criminal behavior; hence, the individual will analyze the costs and benefits of committing a criminal act (Jeffery, 1969, p. 38). Instead of analyzing causal factors of crime that are distal (e.g. community structures), criminality can directly be explained at the behavioural level (Jeffery, 1969, p. 38). Furthermore, under this perspective, proven scientific crime prevention measures are more effective for controlling crime than implementing punishment retroactively (Jeffery, 1969, p. 52, Jeffery & Zahm, 1993, p. 346). Consequently, geographic space is more important than the social ecology of human behaviour. This new criminological perspective “shift[ed] from the sociological to the geographic imagination,” which is now referred to as environmental criminology (Brantingham & Brantingham, 1981a, p. 81). The term environmental criminology includes a wide range of theoretical approaches to explain the spatial aspect of crime (Andresen, 2010, p. 6).

2.3.1. Routine Activity Theory

As mentioned previously, there were significant changes to the economic and sociological structures in American society, especially after World War II. In the post-war era, suburbanization accelerated, and the urban areas were becoming decentralized (Burisk, 1986). More importantly, the overall economic and social conditions were
consistently improving in comparison to previous years (Cohen & Felson, 1979). Despite the improvements to the economy, official reports of property and violent crime drastically increased between 1960 and 1975, (Cohen & Felson, 1979). This relationship between crime and the economy is rather striking because previous theoretical models (i.e. social disorganization theory) predict that socioeconomic conditions will have a negative association with crime. In response to this sociological paradox, Cohen and Felson (1979) argued that “changes in the routine activities of everyday life” directly affects the opportunity for crimes to occur; these criminal opportunities would be referred to as “direct-contact predatory violations” (p. 589). Originally, the authors applied a routine activities approach in order to explain the rise of criminal activity in North America in the mid-twentieth century; however, they did not anticipate the prospects this explanatory model that would eventually develop into a substantial criminological theory.

Routine activity theory is fundamentally different from social disorganization theory because it “focuses on the actions of individuals” and is not concerned with the neighbourhood characteristics at the meso-level (Andresen, 2010, p. 14). Instead, Cohen and Felson (1979) posit that a criminal violation can only occur if three elements converge in time and space: a motivated offender, a suitable target, and the absence of a capable guardian (p. 589). In addition, removing any of these elements from the crime equation would successfully prevent a criminal violation. Cohen and Felson (1979) further argued that previous spatial research has been relatively descriptive and did not consider the temporal interdependences that regulate the ecological nature of human activity.

By incorporating the principles of Amos Hawley’s (1950) work on human ecology, Cohen and Felson (1979) recognized that the temporal components of community structure (rhythm, tempo, and timing) are largely important for understanding the dynamic nature of crime. Considering the community structures in the context of criminal activity, these temporal structures represent the individual travel activity of community members, the total number of “criminal violations per day” at a particular street segment, and the time at which the activity patterns of a victim and an offender intersect (Cohen & Felson, 1979, p. 590) Consequently, the community is conceptualized as “an organization of symbiotic and commensalistic relationships…preformed over both space and time” (Cohen & Felson, 1979, p. 598). In other words, the community is a representation of the interconnected relationships between individual people (Felson & Cohen, 1980, p. 391), as opposed to a static entity or single spatial territory. To have a complete understanding
of the relationship between crime rates and economic conditions, temporal nature of routine activities and criminal violations need to be included in the analyses.

To test routine activity theory and its relation to criminal activity, Cohen and Felson (1979) analyzed survey, consumer, census and criminal victimization data. These researchers hypothesized that economic trends at the micro- and macro- level could effectively alter the criminal milieu and opportunities for crime (Cohen & Felson, 1979). These researchers applied this theory to three different hypothetical scenarios and used multiple data sources to support their hypotheses in order to understand these patterns of crime at the micro-level. First, Cohen and Felson (1979) argued daily activities that occur near the household present a lower risk of criminal victimization than routine activities occurring further away from the household. In the decades following World War II, the rates of employment and recreational engagement had substantially increased (Cohen & Felson, 1979). Because of this sociological trend, there was a greater risk for an offender and a victim to come together in order to complete a criminal violation (Cohen & Felson, 1979). After completing their analyses, they found that people who were walking along a street among strangers had a substantially higher rate of personal larceny than people who were at home with family (Cohen & Felson, 1979, p. 595).

Second, the attractiveness or suitability of a potential target was another factor that could influence criminal behaviour at the micro-level. Consequently, the offender will consider the target’s value, visibility, and accessibility when deciding to complete the criminal act or victimize the target (Cohen & Felson, 1979). When considering this supposition, these researchers assumed that high value products that were easily movable would present a higher risk of being victimized – i.e. automobiles or electronic devices (Cohen & Felson, 1979, p. 595). Cohen and Felson (1979) were able to test this hypothesis by analyzing crime data from the Uniform Crime Report and national data on personal consumption. After the completing the analyses, they concluded that “portable and movable durables [were] reported stolen in great disproportion to their share of the value and weight” in comparison to other products circulating throughout the United States (Cohen & Felson, 1979, p. 596).

Lastly, Cohen and Felson (1979) compared victimization rates between married couples, young adults and adolescents to determine if the routine activities approach could be applicable to micro-level analyses. When applied this approach to individual level
victimization, married couples who engage in family activities near the household are likely to have lower rates of victimization (Cohen & Felson, 1979, p. 596). On the other hand, young single adults who frequently engage in activities away from the household, and young adolescents who engage in peer-group activities outside the household have a greater risk of being victimized (Cohen & Felson, 1979, p. 569). After examining census and survey data, these researchers concluded that single-adult households had higher rates of burglary and robbery, and households that were headed by individuals who were under twenty years of age had a much higher rate of burglary and household larceny (Cohen & Felson, 1979, p. 597).

In addition to applying the routine activities approach to micro-level interactions between individual people, Cohen and Felson (1979) used this theory to explain criminal behaviour at the macro-level. As mention previously, there were many drastic changes to the American sociological structure between the 1960s and 1970s. For instance, college admissions for women, married women entering the labour force and households occupied by single persons had increased by 118, 31 and 34 percent, respectively (Cohen & Felson, 1979, p. 598). As more people were shifting their routine activities away from the household, more houses were being left vacant throughout the day. Under this assumption, daytime burglaries were expected to increase because there was an absence of capable guardians to protect the household. Using census hourly data, these researchers discovered that daytime household vacancy had increased by approximately 50 percent from 1960 to 1971 (Cohen & Felson, 1979, p. 598). Comparing these trends of human activity to criminal activity, the percentage of commercial burglary had decreased from 60 to 36 percent, and the residential burglaries had increased from 16 to 33 percent (Cohen & Felson, 1979, p. 600).

After completing multiple time-series and regression analyses, the results shown that there was a significant relationship between the change in household activities and crime (Cohen & Felson, 1979). Although economic and social developments suggest that criminal motivations should decrease, the change in routine activities had increased the probability for victims and offenders to converge in time and space (Cohen & Felson, 1979). This holds true for both macro- and micro-level data. Thus, the opportunity to commit crime is greater than the motivation to engage in criminal activity. From this, it appears that the opportunity structure for predatory crimes and legitimate activities are mutually dependent upon each other (Cohen & Felson, 1979, p. 605). The increase in
crime, therefore, is not necessarily an indication of social disorganization, but simply a “byproduct of freedom and prosperity” and the routine of everyday activities (Cohen & Felson, 1979, p. 605; Felson & Boba, 2010).

Testing Routine Activities Theory

Although the preliminary analysis of survey and crime data was instructive, there needed to be further empirical analyses in order to show that the key constructs of routine activity theory could be applied to different geographic locations and time periods. Also, other scholars argued that previous attempts to test this theory failed to properly operationalize key concepts that represent different sociodemographic and lifestyle characteristics (Miethe, Stafford & Long, 1987, p. 185). In other words, varying lifestyle choices of the individual person will either increase or decrease the risk of victimization. For example, Miethe and colleagues (1987) created operational constructs representing nighttime and daytime activities from survey data. In addition to prior assumptions of routine activity theory, these researchers hypothesized that individuals who frequently engaged in nighttime activities were at greater risk being victimized than those who participated in daytime activities (Miethe et al., 1987). Furthermore, they included interaction effects into the model in order to determine if activity patterns have a mediating effect on demographics when assessing the risk of victimization (Miethe, et al., 1987). After completing the analyses, the proposed hypotheses were consistent for the results for property offenses, but were not for violent victimization (Miethe et al., 1987, p. 192).

In further studies that investigate the relationship between lifestyle/routine activities and victimization, Sampson and Wooldredge (1987) found further empirical support for this theory. Differing from previous studies, these researchers included community-level variables into their statistical models as well as individual lifestyle characteristics (Sampson & Wooldredge, 1987). For example, the results indicated that guardianship factors, household characteristics and age were related to the burglary victimization (Sampson & Wooldredge, 1987). More specifically at the individual level, households that were occupied by a single person and were left empty for throughout the day had a positive effect on burglary. In contrast, age had negative relationship with burglary, although the effects of age were weaker in magnitude in comparison to the other variables (Sampson & Wooldredge, 1987). When considering the community level context, the following variables had a significant and positive impact on victimization:
housing density, unemployment, family disruption and the single population (Sampson & Wooldredge, 1987). Conversely, the amount of social cohesion within a neighbourhood acted as a protective factor against burglary.

These two studies were important for validating the components of routine activity theory; however, more studies were needed outside the context of American society in order to assess this theory’s generalizability. Within a Canadian context, Kennedy and Forde (1990) adopted the routine activities approach to measure the impacts on various personal and property type offenses. As a methodological strategy, they created different variables representing routine activities, characteristics of potential victims and community structures by using data from a national survey of urban victimization (Kennedy & Forde, 1990). Considering burglary victimization, these researchers found that age had an inverse relationship with this type, and married couples were less likely to be victimized (Kennedy & Forde, 1990, p. 142). With respect to the indicators of routine activities, Kennedy and Forde (1990) discovered that participating in activities away from the household (i.e. attending sporting events, frequently going to bars, restaurants, movie theatres, or work) was a significant predictor of residential burglary. Consequently, these findings support routine activity theory because of the guardianship factor that is needed in order to a house from being burgled. Furthermore, Kennedy and Forde (1990) found similar patterns of victimization for other property crime offenses (e.g. vehicle theft) that supported the routine activities approach.

The final empirical study that is important to mention is Andresen’s (2006) geography of crime study in Vancouver. Andresen’s (2006) research was fundamentally different from the previously mentioned studies because he used census and police data to determine if routine activity theory could be applied to large urban city in western Canada. In addition, this scholar included measures of social disorganization in the analyses and argued that only incorporating these spatial theories in isolation would reduce of the predictive power of the statistical models (Andresen, 2006, p. 501). Using spatial regression and census tracts as a unit of analysis, Andresen (2006) found empirical support for routine activities by using official recorded data, instead of victimization surveys. For instance, average family income (e.g. suitable targets) was an only significant predictor of break and enter incidents in census tracts, whereas the percentage of young persons (e.g. motivated offenders) within a spatial unit had a positive and significant impact on automotive theft and incidents of break and enter (Andresen, 2006, p. 499).
Contrary to expectations, population size (e.g. suitable targets) and population density (e.g. guardianship) had a negative relationship with break and enter and violent crime, but was non-significant for automotive theft (Andresen, 2006, p. 499).

To conclude, routine activity theory has shown to be highly versatile when providing explanations criminal behaviour and victimization at varying levels of analysis. These studies are only a few examples that were able to find empirical support the key theoretical constructs of routine activities. Furthermore, scholars are beginning to apply this theory to contemporary issues within criminology such as cybercrime and cybervictimization (Kigerl, 2011; Pratt, Holtfreter & Reisig, 2010). Although these researchers did not originally foresee the prospects of routine activity theory, Cohen and Felson (1979) originally applied this theory to explain the changing structure of American society and its relation to crime in the mid-twentieth century.

2.3.2. Geometry of Crime

Around the same time when Cohen and Felson (1979) were developing routine activity theory, Brantingham and Brantingham (1981) further contributed to the criminal opportunity perspective by developing the geometric theory of crime. According to Brantingham and Brantingham (1981b), a criminal event encompasses four different dimensions: a law, an offender, a target/victim and a place (p. 7). Similar to routine activity theory, a crime can only occur when all four dimensions coexist with each other within the same time and space (Brantingham & Brantingham, 1981). Without any of these elements, a criminal event cannot occur. As mentioned before, criminological studies have extensively researched the first three dimensions, although the spatial components of crime and its relevance to the concept of place have mostly been ignored to further understand the crime problem (Brantingham & Brantingham, 1981b). Brantingham and Brantingham (1981b) define place “a discrete location in time and space at which the other three dimensions intersect and a criminal event occurs” (p. 8). In addition to the aspects of place, environmental criminologists are particularly interested in “the physical and social characteristics of [the] crime site” and “the spatial distribution of targets and offenders” within urban settings (Brantingham & Brantingham, 1981, p. 8). Consequently, criminological research should determine the impact of the urban environment and geography on crime and criminal opportunities, instead of the focusing on sociological concepts.
Influenced by environmental psychology and urban geography, Brantingham and Brantingham (1981) argued that the environmental backcloth will significantly affect the amount of criminal activity in a specific area. The environmental backcloth is a concept used to illustrate the movement and change within a geographic landscape, and is often referenced to place characteristics, such as road networks, land developments and the socioeconomic status of residents/workers (Brantingham, Brantingham & Andresen, 2017). To further describe and explain the environmental backcloth, these scholars used the idea of a flag to help illustrate this concept. Within a two-dimensional context, a flag is a stationary object that represents different symbols, emblems and colours; however, within a three-dimensional framework when there is wind blowing, the flag will to wave in the wind and display different movement patterns (Brantingham & Branthingham, 1993). Given a real-life example, individuals might will have different perceptions of the environment when walking along the streets of a city’s entertainment district or skid-row at noon on in the middle of the week, as oppose to the two o’clock in the evening on a Friday night (Andresen, 2014). It is likely that there will be an increased perception of danger and fear of crime in the latter scenario compared to the former. Although the spatial aspects of each scenario are the same, the environmental backcloth changes the criminal context when considering the temporal changes of the physical space.

Adopting the rational choice framework, the Brantingham’s (1981) further utilized their theory to provide explanations for offender decision-making. In essence, they argued that criminal motivation simply exists, but the motivation to commit crime will vary among different individuals (Brantingham & Brantingham, 1981). In theory, therefore, the environment will emit certain signals or cues that will influence an individual’s decision-making process to engage in or desist from criminal activity (Brantingham & Brantingham, 1981b, p. 233). If a person is criminal motivated, then that individual will learn to identify which social cues within the environment are “associated with [suitable] victims or targets” through social transmission or personal experience (Brantingham & Branthingham, 1981b, p. 233). As a result, the offender will develop a specific crime template that dictates future search patterns. However, there are likely to be multiple crime templates because offenders, targets and victims are not uniformly distributed across time and space. Instead, these elements are likely clustered around different places within the environment that attract different human activities (Brantingham & Brantingham, 1981b, p. 233). Just like routine activity theory, the framework for geometry theory of crime is centred on the
notion that criminality is interconnected with non-criminal activities. For instance, offenders will spend most of their time engaging in non-criminal behaviours because it would be rather exhausting and inefficient to constantly commit crime at every moment in time. Because humans are creatures of habit, offenders will decide to commit their crimes within and around areas that they are familiar with and where they spend most of their time - i.e. home, work, recreational and entertainment centres (Brantingham & Brantingham, 2008). If offenders are spending most of their time preforming regular non-criminal activities, it is more likely that offenders will come in contact with potential targets and victims at these non-criminal places. Consequently, crimes are expected to cluster around major activity nodes and major pathways that attract human activity because victims and offenders have a higher probability of converging in time and space at these places (Brantingham, et al., 2017).

**Crime Generators and Attractors**

As a practical implication for this theory, Brantingham and Brantingham (1995) designated these high-risk activity nodes as crime generators and crime attractors. Crime generators are certain places that attract large numbers of people for reasons that are unrelated to criminal activity (Brantingham & Brantingham, 1995). Examples of such would include shopping and entertainment districts, or areas with a concentration of commercial offices (Brantingham & Brantingham, 1995). Crime generators can also form at major travel nodes, such as transit stations, bus interchanges, and parking lots around the vicinity of transit stations (Brantingham & Brantingham, 1995). Consequently, because of the high concentration of people at particular times and places, crime generators are expected to produce more opportunities for crime than places that attract less people (Brantingham et al., 2017, p. 108).

In contrast, crime attractors are “particular places, areas, neighbourhoods, [or] districts” that are well-known for having a plethora of criminal opportunities (Brantingham & Brantingham, 1995, p. 8). Therefore, these areas and activity nodes become known for attracting motivated and repeats offenders (Brantingham & Brantingham, 2008, p. 89). For example, drug markets, bar districts, prostitution areas, large shopping malls, areas around major transit stations, and parking lots with limited security measures are attractive places for criminals to engage in criminal activity (Brantingham & Brantingham, 1995). Consequently, a motivated offender will travel to these places for the sole intention of
committing crime because of the abundance of suitable targets. It is also noteworthy these concepts are not mutually exclusive, because particular places are not likely to be only consist of crime generators or attractors. Instead, most areas will be a mix of both attractors and generators, and some areas will only attract certain types of crime (Branthingham & Brantingham, 2008, p. 90).

As an empirical test of these theoretical concepts, Kinney and colleagues (2008) used crime and land-use data to investigate the validity of these concepts. Overall, these researchers found that the patterns of crime were associated with the patterns of human activity with the city (Kinney et al., 2008). For instance, areas with had a regional shopping centre within the geographic boundaries had more incidents of assault and motor vehicle theft. Further, areas with schools and universities, and parks and playing fields appeared to generator more opportunities for motor vehicle theft (Kinney et al., 2008). In a more recent study, Bernasco and Block (2011) were able to operationalize these concepts more directly at smaller spatial units of analysis. For example, crime generators were operationalized as bars, clubs, liquor stores, commercial businesses, etc. On the other hand, crime attractors were areas with illicit activity known to police, such as illegal markets, gang and drug activities and prostitution soliciting (Bernasco & Block, 2011). After running the analyses, these researchers found that many of their variables had a significant effect on increasing the number of street robberies within the surrounding street blocks (Bernasco & Block, 2011).

In another empirical study, Groff and McCord (2012) sought to further investigate the relationship between public parks and crime to determine if parks could act as crime generators. Not only did they determine that parks generated more crime in the surround areas, but Groff and McCord (2012) also found that the specific characteristics of the park increased or decreased the risk of crime. In the Canadian context, Demeau and Parent (2018) examine the relationship between four different types of crime and crime generators/attractors in Montreal. In addition to the crime generator/attractor variables, these researchers also include socio-demographic variables into the model as control variables (Demeau & Parent, 2018). Just like the previous studies, Demeau and Parent (2018) found empirical support for these theoretical concepts; many of the variables in the model had a significant and positive effect on assaults, thefts, robberies and motor vehicle thefts.
2.4. Conclusion

The development of spatial criminology has undergone drastic changes over the past two hundred years. Early spatial research in the nineteenth century provided macro-level explanations of crime (i.e. country and state-level), whereas research in the early twentieth century developed meso-level theories that focused on analyzing neighbourhood characteristics. Lastly, in the late twentieth century, scholars examined the opportunities structures that were conducive to criminal activity in order to explain the individual-level interactions between motivated offenders and potential targets. As time progressed and these theories became more established in the literature, scholars began to separate themselves into two different camps of empirical research in spatial criminology: social disorganization and criminal opportunity perspectives (i.e. routine activity theory and geometry of crime). As some research has shown, however, it would beneficial to adopt a framework for theoretical integration, as opposed to theoretical competition in order to makes advances in spatial criminology (Smith et al., 2000; Weisburd et al., 2012).
Chapter 3.

Crime and Place Empirical Research

The following chapter will focus on the fourth wave of spatial crime research that was mentioned in the previous chapter. Specifically, this section will review the empirical literature on the concentration of crime at micro-places and demonstrate how scholars have attempted to apply these spatial criminological theories at micro-places. Furthermore, there will be discussion on the how the units of analysis in spatial criminological have progressively become smaller throughout time and review the literature that has been able to determine which place features have an impact on certain types of crime.

3.1. The Criminology of Place – Literature Review

It has been well established in the criminological literature that criminal events are spatially patterned across different geographic landscapes. Throughout the development of spatial criminology, the units of analysis have become progressively smaller (from countries to neighbourhoods) and the spatial crime theories have evolved over time. Within the historical context, spatial crime research has primarily focused on addressing the effects of neighbourhood structural characteristics on criminal activity and victimization (Sampson & Groves, 1989; Shaw & McKay, 1942). These studies have traditionally placed emphasis on large spatial units, such as neighbourhoods or census tracts. However, scholars have now determined that neighbourhoods exhibit spatial variation and crime is highly concentrated at smaller areas or ‘hotspots’ (Sherman et al., 1989). Because crime is highly concentrated, it would be misleading to make inferences from aggregate-level data and it provide an inaccurate representation of criminal activity (Andresen, 2014; Andresen & Linning, 2012). Consequently, these macro-level studies have a higher risk of committing the ecological fallacy (Robinson, 1950). As the decades progressed and technology has become more sophisticated, the increase in computational power has enabled researchers to move down the geographic cone of resolution (Brantingham, Dyerson & Brantingham, 1976) in order to study and analyze micro-spatial units. Empirical research that utilizes these micro-places as the spatial unit of analysis is often referred to as the crime and place literature. In context of
micro-spatial research, places are referred to as “specific locations within the larger social environment” (Eck & Weisburd, 1995, p. 3). Therefore, crime and place scholars are interested in how crime patterns emerge at discrete addresses, city blocks or street segments and intersections.

The first empirical study to investigate the concentration of crime was conducted by Lawrence Sherman and colleagues (1989). These researchers analyzed over 300,000 police incident data at 115,000 street addresses and intersections in Minneapolis (Sherman et al., 1989). Further, their conceptual definition of a micro-place was identified as a discrete address. The results indicated that 50 percent of the calls for service were distributed across 3 percent of the places throughout the city (Sherman, et., 1989). In further analyses, the researchers demonstrated that predatory crimes such as robbery, rape and auto theft were concentrated at an even small number of places – 2.2 percent, 1.2 percent, and 2.7 percent, respectively (Sherman et al., 1989). In addition, Sherman and colleagues determined that certain criminogenic places (e.g. bars, parks, convenience stores, retail outlets) attracted more criminal activity. These findings supported the argument against using community-level data for spatial analyses. Because these researchers discovered that crimes were occurring at only a few discrete locations, analyses that involved aggregate census data would not have been able to uncover these patterns of criminal ‘hot spots’. Furthermore, most neighbourhoods would be relatively crime-free because of this high variation of crime within the neighbourhood (Sherman et al., 1989). Therefore, areas that are colloquially labelled as ‘bad’ neighbourhoods would have crime-free places, whereas ‘good’ neighbourhoods would have relatively few high-crime places. This novel research established the need to investigate the “criminology of place” and further understand how places are criminogenically different or distinct from neighbourhoods (Sherman et al., 1989, p. 44). Although this study was instructive, the inferences drawn from the results were limited because of the cross-sectional nature of the study.

Over a decade later, Smith and colleagues (2000) further contributed to the crime and place literature by integrating social disorganization and routine activities theory. The authors acknowledged that previous attempts of integrating these theories were relatively unsuccessful because past studies analyzed units that were too coarse to make accurate inferences – i.e. neighbourhoods, census tracts, multiple city blocks (Smith et al., 2000). However, Smith and colleagues (2000) were able to produce empirical support for
integrating these two theories because they used street segments as a unit of analysis to represent micro-places – they used the term face blocks instead of street segments (Smith et al., 2000). Moreover, these researchers created multiple variables to represent social disorganization and routine activity theory by using tax assessment and census data. Additionally, they included interaction effects into the regression model by creating cross-product terms between the social disorganization and land-use variables (Smith et al., 2000). After completing the analyses, Smith and colleagues (2000) were able to determine that many their indicators and interaction effects had a significant relationship with street robberies in the theoretically expected direction. Moreover, these researchers identified that “social disorganization and routine activity variables have…contingent [effects] on one another;” however, these interacting effects were only identifiable at the micro-spatial level (Smith et al., 2000, p. 516). Arguably speaking, the inherent spatial heterogeneity within larger spatial units is a potential reason why previous theoretical integration was largely unsuccessful.

3.1.1. Street Segments, Developmental Trajectories and Crime - Seattle, WA

Prior studies that investigated the concentration of crime at micro-places have primarily relied on cross-sectional data (Weisburd, Bushway, Lum & Yang, 2004). Consequently, these studies that analyzed crime data crime over shorter periods of time were not able to provide enough empirical evidence to significantly impact or influence theory or criminal justice policy (Weisburd et al., 2004, p.306). In response to these limitations, Weisburd and colleagues (2004) conducted a longitudinal study that examined incident police data from Seattle, Washington, over a fourteen-year period and conducted a group-based trajectory analysis. This statistical method is predominantly used in developmental criminology in order to identify the developmental trends of criminal offending over the life-course of a criminal offender (Nagin & Land, 1993). Specifically, this method is used to classify individuals within the sample into different clusters “with similar developmental trajectories and...to study patterns of change in offending and aggression as people age” (Weisburd et al., 2004, p. 296). At the time, applying this statistical technique to street segments was an innovative and novel approach to obtain greater insights and to further understand “the development of crime at places over time” (Weisburd et al., 2004, p. 286). Within the same year, other scholars were utilizing this
same technique to advance spatial-temporal methodologies, but conducted the analyses at higher levels of geography (Griffiths & Chavez, 2004).

Overall, the Seattle study validated the assumptions and findings of previous empirical research into micro-places. Weisburd and colleagues (2004) found that crime was “tightly clustered in specific places within urban areas” and most places throughout the city did not experience any criminal activity or in general had very little crime over an extended period of time (p. 310). Similar to the findings of the Minneapolis study, 50 percent of criminal incidents were concentrated at only 5 percent of street segments throughout Seattle (Weisburd et al., 2004). At an even more precise scale, only 1 percent of street segments in Seattle had over fifty criminal events each year throughout the total fourteen-years of the study (Weisburd et al., 2004).

To further identify the developmental patterns of crime that street segments experienced over time, the trajectory analysis was used to determine which street segments had stable, increasing or decreasing crime patterns. From the analysis, the authors identified eighteen different group trajectories (Weisburd et al., 2004). Further, they discovered that eight of the eighteen trajectories were defined as stable trajectories, which consisted of 84 percent of the street segments from the entire (Weisburd et al., 2004). In other words, there was no statistically significant difference in the change of crime for each street segment over time. Three group trajectories were identified as being an increasing trajectory and only consisted of roughly 2 percent of the street segments (Weisburd, et al., 2004). Interestingly, one of the trajectories in this group started with a very low crime rate and steadily had an increase crime rate of 20 incidents per year. Furthermore, the average crime rate for this trajectory had become four times greater at the end of the study in comparison to the beginning of the study (Weisburd et al., 2004, p. 302). Lastly, the remaining seven groups were classified as a decreasing trajectory, which accounted for around 14 percent of streets in Seattle (Weisburd et al., 2004). Similar to the increasing trajectories, the rate of change in crime within the decreasing trajectories was relatively large. For example, one of the decreasing trajectories had roughly 95 criminal incidents at the beginning of the study and had decreased to average rate of 75 crimes at the end of the study (Weisburd et al., 2004).

These findings were rather interesting because Weisburd and colleagues (2004) noted that the decreasing trajectories accounted for a large proportion of the overall drop
in crime in Seattle. Therefore, it appears that the crime drop was largely affected by a small percentage of street segments, as opposed to an overall drop that occurred uniformly throughout the city (Andresen, 2014). Overall, the Seattle study was monumental to the development of crime and place because it demonstrated that crime was in fact highly concentrated to a small number of micro-place and that these patterns were relatively stable over time (Weisburd et al., 2004).

After the Seattle study, there was a sudden increase in crime and place studies that were interested in uncovering these patterns of high concentration at street segments. Despite this growth in the academic literature, scholars had largely neglected or failed to consider the importance of examining the geographic locations of juvenile delinquency. Consequently, criminological researchers had not been able to make a distinction between adult and juvenile offenses (Weisburd, Morris & Groff, 2009). Specifically, the locations in which adults and juveniles decide to commit their crimes. To address the gaps in the literature, Weisburd and colleagues (2009) utilized a trajectory analysis and applied this method to official records that reported the quantity and location of juvenile arrest incidents. Applying the framework of routine activity theory, these researchers predicted that juvenile crimes will be even more concentrated at specific places than adult crimes because youth likely have limited activity spaces that they are familiar with and visit frequently (Weisburd et al., 2009).

Completing their analyses over a fourteen-year timeframe in Seattle, Weisburd and colleagues (2009) were able to confirm their prior predictions of high concentration of crime and found preliminary support for the application of routine activity theory to juvenile crimes. The results showed that juvenile crimes in Seattle were far more concentrated than adult crime and that juvenile crimes within this city had decreased by 41 percent from 1989 to 2004 (Weisburd et al., 2009). For example, all incidents of juvenile arrests occurred at only 3 to 5 percent of street segments within a given year and less than 1 percent of street segments had 50 percent of juvenile arrests (Weisburd et al., 2009). This provided some circumstantial evidence to the support the notion that youth have limited activity spaces when deciding where to commit their crimes. To further test these assumptions, these researchers found that trajectories with higher rates of arrests were more likely to have an arrest incident occur at schools, youth centres, retail shops and malls, and restaurants, in comparison to the other trajectories (Weisburd et al., 2009).
More specific to the trajectory analysis, these researchers identified eight different trajectory groups, but many of these trajectories had “very little or no juvenile crime” throughout study period (Weisburd et al., 2009, p. 454). Even further, approximately 89 percent of all street segments were classified into one trajectory group, although the streets in this group could only account for 12 percent of the arrests for the entire study. As for the other trajectories, three groups had a substantially higher number of arrest incidents, but only include 0.29 percent of the street segments throughout the city (Weisburd et al., 2009, p. 454). However, these marginally small group of street segments had about one-third of all juvenile arrests throughout the study period (Weisburd et al., 2009). Moreover, the spatial patterns of juvenile crimes were relatively stable over the fourteen-year period, similar to criminal adult offending in Seattle (Weisburd et al., 2009).

Building off the Seattle study of juvenile crime, Groff and colleagues (2009) further investigated the spatial patterning and clustering of street segments within the trajectory groups using the same juvenile offending dataset. Using quantitative spatial statistics and geographic information systems, these researchers found that “places in the same trajectory group” were distributed throughout the entire city (Groff, Weisburd & Morris, 2009, p. 81). Furthermore, they found that street segments of the same trajectory group were collocated with each other throughout Seattle, therefore demonstrating that the distribution was not random (Groff et al., 2009). Surprising to these researchers, the increasing and decreasing trajectory groups exhibited more local spatial clustering than expected. With respect to another unexpected finding, street segments that were adjacent from each other displayed very different crime trends over time and on some occasions had completely opposite temporal crime trends (Groff et al., 2009). This appeared to be highly unusual because this trend within the data violated Tobler’s (1970) first law of geography that near places should be more related to each other than distant places.

To further investigate this phenomenon of spatial variability and complement these findings, Groff and colleagues (2010) used the same statistical methods to analyze the same police data from the original Seattle study. However, in the more recent study, they added two more years of data to expand it into a longitudinal study of sixteen-years (Groff, Weisburd & Yang, 2010). Just like the previous Seattle juvenile study, adult crimes in Seattle displayed similar spatial clustering patterns (Groff et al., 2010). Street segments within the same trajectory were collocated around the same general areas within the city; however, the temporal patterns of crime varied significantly when examining adjacent
street segments (Groff et al., 2010). This street to street variability was rather interesting because it would mean that something happening at the micro-spatial level that causes certain street segments to have a chronic crime problem. Perhaps street segments do in fact have unique ‘behaviour settings’ and function differently than the overall community. However, specific data describing the features and characteristics of street segments are needed in order to make accurate inferences.

3.1.2. Homicides, Gun Violence and Robberies at Street Segments - Boston, MA

These past research studies have created a solid foundation and have made great strives to produce empirical evidence to support the notion that crime is highly concentrated at a small number of places. However, previous research had only examined aggregate crime data and did not analyze disaggregate or specific crime types. Several criminologists within the crime and place field have attempted to address these gaps in literature by using various methods and different data sources. Firstly, Braga and colleagues (2010) conducted a longitudinal study in Boston to investigate the patterns of gun violence at street segments and intersections over a twenty-nine year period. Specifically, they defined gun violence as homicides precipitated by a firearm or causing serious bodily-harm with a firearm (Braga, Papachristos & Hureau, 2010). To identify the developmental patterns of gun violence over time, these researchers utilized growth curve regression models to classify the different trajectories (Braga et al., 2010).

Braga and colleagues (2010) found that gun violence in Boston over time was not uniformly distributed across the city, instead these crimes were highly concentrated at a very small number of street segments and intersections. Of these places that experienced gun violence, the analysis was able to identify two general trajectories: stable and volatile concentration. Interestingly, the places that were classified as having volatile trajectories produce more than 50 percent of all gun violence, but were only represented by less than 3 percent of street segments and intersections throughout the entire city (Braga et al., 2010). Even more interesting, these small number of volatile places appeared to have the largest impact on affecting the overall trends of gun violence in Boston (Braga et al., 2010). This finding is consistent with Weisburd and colleagues’ (2004) discovery in Seattle – only a small percentage of places were responsible for the city’s overall drop in crime. Although
this pattern was only found in two different studys, it would appear that only a small number of places within any particular city would affect the citywide trends of crime.

Moving forward, Braga and colleagues (2011) completed another longitudinal study Boston within the same time period between 1980 and 2008. In the current study, however, the outcome variables included different types of robbery, instead of gun violence (Braga, Hureau & Papachristos, 2011). Specifically, this crime type was disaggregated into four different categories: street, commercial, other and total robbery incidents. Once more, these researchers used streets segments and intersection as the unit of analysis and applied growth curve regression to identify the different temporal patterns of crime over time (Braga et al., 2011). After completing the analyses, the models classified streets segments into three separate groups: low, medium and high levels of robbery incidents. When examining the frequency distribution of the all types of robbery, the results revealed that street, commercial and total robbery incidents occurred at a disproportionately small number of street segments (Braga et al., 2011). For example, 8.8 percent of places in the city produced 68.2 percent of total robbery incidents; 65.6 percent of street robberies occurred at only 8.3 percent of street segments and intersections (Braga et al., 2011, p. 23). Furthermore, 9.1 percent of street units produced all commercial robberies and only 1.3 percent of places generated approximately 50 percent of commercial robberies throughout Boston over the twenty-nine year period (Braga et al., 2011). The results of the two Boston studies further support the findings of the Seattle study (Weisburd et al., 2004) and emphasize the importance of analyzing crime patterns at micro-places.

3.1.3. Place-based Criminological Research in Canada

**Measuring the Concentration of Crime - Vancouver, BC (2011)**

Despite the increasing support for the concentration of crime at places for various types of crime, it was uncertain that these results could be generalizable to different geographic locations outside the United States. To further contribute to the literature, several scholars sought to resolve these concerns within a Canadian context. Andresen and Malleson (2011) were the first set of researchers to conduct a crime and place study outside of the U.S. by analyzing police incident data from Vancouver, British Columbia. Similar to the Weisburd et al. (2004), these researchers completed a longitudinal study
over a ten-year period. However, instead of only including aggregate level crime data into the analyses, Andresen and Malleson (2011) were able to disaggregate the data into seven different crime types. The crime data were separated into the following classifications: assault, burglary, robbery, sexual assault, theft, theft of vehicle, and theft from vehicle (Andresen & Malleson, 2011). Furthermore, these researchers completed the analyses at three different levels of geography, which was another distinction from the original Seattle study. The purpose of using different spatial units of analysis was physically demonstrate how the analyses could produce different results at census tracts, dissemination areas or street segments (Andresen & Malleson, 2011). Lastly, to move beyond replication and extend the results of previous crime and place studies, these scholars utilized an innovative statistical method at the time. Originally developed by Andresen (2009), this method is a non-parametric point pattern test that measures the similarities between two spatial areas at the local level (Andresen & Malleson, 2011).

The results showed that crime in Vancouver was also highly concentrated at a small number of street segments, although the degree of concentration varied depending on the year and crime type. For example, 50 percent of robberies occurred at less than one percent of street segments, whereas 50 percent of burglaries were reported at approximately 8 percent of street segments throughout the city (Andresen & Malleson, 2011). It is also noteworthy that the percentage of concentration was relatively stable over the entire study period. In addition to these percentages, Andresen and Malleson (2011) also reported the percent of street segments that experienced at least one criminal incident for each crime classification. For instance, roughly 50 percent of streets had at least one incident of burglary or theft from vehicle in 1996, however about 5 percent of streets had an incident of robbery or sexual assault in 1996 (Andresen & Malleson, 2011). In other words, around 95 percent of places in Vancouver were relatively free of the latter two crimes. The high degree of variation is probably due to the rarity and predatory nature of robbery and sexual assault, whereas property crimes are much more prevalent in Vancouver.

As for the spatial point pattern test, the results were used to interpret the temporal stability of crime patterns over time. Starting with the highest level of geography (e.g. census tracts), the spatial crime patterns were not stable over time for any of the crime classifications (Andresen & Malleson, 2011). On the other hand, several of the crime classification showed a higher degree of similarity between spatial units when the test was
applied to dissemination areas. Even further, almost all seven crime classifications demonstrated patterns of spatial stability when conducting the analysis at street segments (Andresen & Malleson, 2011). The change in stability was especially striking for robbery and sexual assault when comparing the results from census tracts to street segments. Most importantly, crimes appeared to be more stable over time when the analyses incorporated smaller spatial units (Andresen & Malleson, 2011).

To further validate these findings, these researchers conducted a sensitivity analysis by repeating the spatial point patterns with nonzero spatial units at all three scales of geography. By definition, a nonzero spatial unit included a census tract, dissemination area, or street segment that had at least one criminal incident over the time period (Andresen & Malleson, 2011). After completing the sensitivity analysis, the results did not significantly change from the initial tests (Andresen & Malleson, 2011). Consequently, Vancouver study provided additional empirical support for the concentration of crime at micro-places. Additionally, these results further supplemented the argument for using smaller spatial units because important information about the patterns of crime would have gone undetected if the analyses only included higher levels of geography.

**Further Testing the Concentration of Crime - Ottawa, ON (2012)**

In another Canadian crime and place study, Andresen and Linning (2012) compared the percent of crime concentration between Vancouver, B.C. and Ottawa, Ontario. Using similar methodologies and analytic strategies as the previous Vancouver study (2011), the data from the current study showed that crime was much more concentrated in Ottawa than it was in Vancouver. For instance, less than 2 percent of the street segments represented 50 percent of the total criminal incidents; 50 percent of robbery incidents (aggregate) were concentrated at less than 0.5 percent of places in Ottawa (Andresen & Linning, 2012). Furthermore, roughly 1.5 percent of places had 50 percent of break and enter incidents (aggregate); and 50 percent of theft of vehicle occurred at 1 percent of street segments in the city (Andresen & Linning, 2012). Furthermore, more than 90 percent of places in Ottawa did not experience any incidents crime (Andresen & Linning, 2012). As for the specific crime types, the percentage of streets that had at least one crime incident varied from 0.30 percent (commercial robbery) to roughly 5 percent - residential break and enter (Andresen & Linning, 2012).
Next, running the spatial point pattern test with Ottawa crime data yielded similar results as the Vancouver study. For example, when conducting the analysis at census tracts, individual crime types and the aggregate crime types had very low indices of similarity (S-index). Specifically, the ‘total crime’ variable generated the smallest values (Andresen & Linning, 2012). For the analysis on dissemination areas, on the other hand, many of the individual crime types had a S-index that reached the value of 0.80, which was the threshold used to indicate spatial similarity (Andresen & Linning, 2012). Although the S-index was higher than the census tracts, the ‘total crime’ variable still produced a relatively low value for the S-index (Andresen & Linning, 2012). When considering street segments as the unit of analysis, all individual crime types and all aggregate level crime data had a S-index of over 0.80. Consequently, the results showed that it is important to disaggregate the crime data if researchers are interested in uncovering the spatial pattern of different polygon units (i.e. census tract or dissemination areas). Completing the analyses with only aggregated crime data with masquerade the true spatial crime patterns; however, this issues does not appear to be a problem if the units of analysis are microspatial units (Andresen & Linning, 2012). Overall, crime in Ottawa displayed similar patterns of concentration as the previous crime and place studies (Andresen & Linning, 2012, p. 278).

**Replicating the Developmental Trajectories of Street Segments – Vancouver, BC (2015)**

During this time, no other criminological researchers had directly replicated the study conducted by Weisburd and his colleagues (2004) outside of Seattle by using the same statistical methods. Because of that, Weisburd and colleagues (2012) called on other crime and place scholars to produce replication studies to find out if the results from Seattle can be generalizable to other municipalities. In order to address this issue, Curman and colleagues (2015) utilized the same statistical techniques as Weisburd et al. (2004) – i.e. group-based trajectory modeling (GBTM) – with calls-for-service data from the Vancouver Police Department. However, Curman and colleagues (2015) acknowledged that GBTM might not be appropriate for the spatial analysis of crime because this method requires that the data to fit a specific distribution and follow certain assumptions. For example, GBTM assumes that the observations are independent from each other over time. This might be problematic because spatial units of analysis are often spatially dependent of its neighbours (i.e. spatial autocorrelation). Consequently,
inaccurate inferences may be drawn from the data since GBTM does not account for the spatial dependencies within the data (Curman et al., 2015). Further, the software used to conduct this analysis cannot accommodate counts over fifty for each unit of analysis (Curman et al., 2015). When an observation has a value over fifty, the software will truncate those cases at fifty, therefore potentially leaving out important information from the analysis (Curman et al., 2015). This often occurs in spatial crime analysis, however, this situation only affected 3.6 percent of street segments in the Vancouver dataset (Curman et al., 2015). Therefore, to supplement the finding from the GBTM, these scholars used k-means cluster analysis because this technique requires less assumption of the data (Curman et al., 2015).

Completing the study over a sixteen-year period, the results from the Vancouver longitudinal study produced similar levels of concentration as previous research. For example, all calls for police service were generated from 50 to 60 percent of the street blocks and 50 percent of the police data came from 4.5 to 7.8 percent of the street blocks (Curman et al., 2015). Turning to the GBTM, the analyses from Vancouver yielded fairly similar results as the Seattle study, although there were some notable differences as well. For instance, the GBTM identify a seven-group solution in Vancouver, as oppose to an eighteen-group solution in Settle. This discrepancy is probably attributed to the differences between both datasets; the Settle study included all crime incidents into the analysis, whereas the Vancouver study only twenty-two different indices of property and violent offenses (Curman et al., 2015).

To identify which trajectories were stable, increasing or decreasing, Curman and colleagues adopted the criteria used by Weisburd et al. (2004). Of the seven-group solution in Vancouver, three were classified as stable trajectories (70 percent of street blocks), four were decreasing (30 percent of street blocks), and none were considered as an increasing trajectory (Curman et al., 2015). The percentage of street blocks in each trajectory were very similar to the Seattle study, expect that Vancouver did not experience any increasing trajectories (Curman et al., 2015). As for the k-means cluster analysis, the results indicated that a four-group solution was the best fit for the data. Of these four groups, one group was identified as a stable trajectory (94 percent of streets) and three groups were classified as a decreasing trajectory (Curman et al., 2015). Other than these minor differences, the results were qualitatively the same when comparing the Vancouver
study to the Seattle Study, and comparing the results of the GBTM and k-means cluster analysis in Vancouver.


As the number of place-based studies were gradually increasing and the evidence became even more compelling, Weisburd (2015) argued that criminological research should be take a new turn in a new direction to further understand criminality and deviance. In his presidential address to the American Society of Criminology, Weisburd (2015) strongly suggested that more research is need that considers the micro-geographies as the unit of analysis. By gathering empirical articles that were published in *Criminology* from 1990 to 2014, he found that person-based research had dominated this academic journal (66.1%); however, only a fraction of those articles examined micro-places - 4.3% (Weisburd, 2015). Failing to consider these micro-places and hot spots of crime could prevent scholars from having a holistic understanding of the crime problem.

Because of the developing field of placed-based research, Weisburd (2015) uses previous empirical research as evidence to suggest that there is a *law of crime concentration*. Being the first law of the criminology of place, his proposition was stated as the following: “a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime” (Weisburd, 2015, p. 138). To guide and inform future research, this ‘bandwidth of percentages’ is defined as the “specific cumulative proportion of crime” that would be used as a standard unit of measurement to determine the levels of crime concentration (Weisburd, 2015, p. 138). Specifically, these narrow bandwidths are specified measurements of 25 or 50 percent of crime throughout the city (Weisburd, 2015).

To further provide support for this proposition, Weisburd (2015) used examples from empirical studies from eight different jurisdictions: five large urban cities (i.e. Sacramento, CA; Cincinnati, OH; New York, NY; Seattle, WA and Tel Aviv-Yafo) and three small suburban cities (i.e. Brooklyn Park, MN; Redlands, CA and Ventura, CA). Of the urban cities, it appears that 50 percent of crime is highly concentrated at a small
number of street segments. For example, the levels of concentration ranged from 4.2 percent (Sacramento, CA) to 6.0 percent (Cincinnati, OH). As for the 25 percent bandwidth, the percentage of crime concentration ranged from 0.8 percent (Sacramento, CA) to 1.6 percent (Cincinnati, OH). Turning to the suburban cities, the levels of crime are even more concentrated than the urban cities at the 50 and 25 percent bandwidth. For instance, crime concentration for the 50 percent bandwidth ranged from 2.1 percent (Brooklyn Park, MN; Redlands, CA) to 3.5 percent - Ventura, CA (Weisburd, 2015). Lastly, 0.4 percent (Brooklyn Park, MN; Redlands, CA) and 0.7 percent (Redlands, CA) had experienced 25 percent of the crimes throughout the entire city (Weisburd, 2015). Therefore, as a rough estimation and a general rule, 50 percent of crimes should roughly be located at 5 percent of places, and 25 percent of crime should approximately be generated by 1 percent of the places. Although the author acknowledged that the sample was gathered through a matter of convenience and not through random sampling methods, the findings from each city are rather compelling and have strong implications for criminal justice policy (Weisburd, 2015). To supplement these findings with stronger empirical evidence, perhaps criminological scholars could perform meta-analytic studies by incorporating the results from previous crime and place research.


To accomplish Weisburd’s (2015) research agenda, the Journal of Quantitative Criminology published a special issue volume that included several empirical investigations into the law of crime concentration. In a practical sense, the law of crime concentration should be used as an analytical framework to “enhance our theoretical understanding of the crime problem” and to develop evidence-based crime prevention initiatives that target “persistent problem places” (Braga, Andresen & Lawton, 2017, p. 422). Andresen and colleagues (2017) expanded the previous Vancouver study (2015) by the disaggregating the data into seven different crime types. Using k-means clustering to identify the developmental trajectories, the results support the law of crime concentration and found that the trajectories were stable over time (Andresen, Curman & Linning, 2017). In fact, these scholars further acknowledge that the rule of ‘5 percent places represent 50 percent of criminal activity’ might be too conservative when the analyses include disaggregated crime data (Andresen et al. 2017). In another article,
Bernasco and Steenbeck (2017) argued that a standard methodology is needed when other researchers are attempting to measure the concentration of crime. Since there will almost always be more places than incidents of crime, other statistical methods might produce biased estimates because of this unequal distribution of crime in micro-spatial studies (Bernasco & Steenbeck, 2017). Using police incident data from the Hague, Bernasco and Steebeck (2017) were able to demonstrate that the generalized Lorenz curve and Gini coefficient can uncover the processes of crime concentration more accurately.

To apply Bernasco and Steenbeck's (2017) suggested methodological practices for crime and place investigations, Schnell and colleagues (2017) utilized Lorenz curves, Gini coefficients, and linear mixed models to test the law of crime concentration. Further, these researchers analyzed data on violent crimes from Chicago, IL, over a fourteen-year period at three different spatial scales: community areas, neighbourhood clusters and street segments (Schnell, Braga & Piza, 2017). From the results, they found that 20 percent of neighbourhood clusters and community areas were responsible for 50 percent of violent crime, whereas 50 percent of violent incidents were found at approximately 5 to 7 percent of street segments (Schnell et al., 2017). Importantly, these researchers discovered that street segments were an attributing factor to the amount of variation in violent crime throughout the city - 56 to 65 percent (Schnell et al., 2017). Consequently, these results provide further evidence to suggest that important information about the spatial patterns of crime would have been lost if the analyses were only conducted with large spatial units.

To further investigate the law of crime concentration at places, Hibdon and colleagues (2017) sought to examine the distribution of drug activity in Seattle, WA over a 5-year period with calls-for-service data (police and ambulance data). By using multiple statistical methods, the data appeared to display similar patterns of concentration for drug activity – 2 percent of street segments were responsible for 50 percent of the calls-for-service (Hibdon, Telep & Groff, 2017). After completing the trajectory analysis, most groups experienced stable patterns of drug crime and over 50 percent of street segments did not have any recorded drug crimes over the five-year period (Hibdon et al., 2017). However, these researchers discovered that the local stability patterns of drug activity were only moderately stable (Hibdon et al., 2017). Lastly, Haberman and colleagues (2017) analyzed police incident data (e.g. street
robberies) at street segments and intersections in Philadelphia, PA. Using a different approach than the pervious empirical studies, they tested the law of crime concentration at different temporal scales that are relevant to criminological theory – hours within the day, days of the week, and seasons of the year (Haberman, Sorg & Ratcliffe, 2017). Overall, these researchers found empirical support for applying the 25 and 50 bandwidths specified in the law of crime concentration at different temporal scales (Haberman et al., 2017). These scholars further argued that more studies within the crime and place literature need to included temporal factors into the analysis to obtain a greater understanding of the crime problem.

3.4. Place Features and Criminogenic Facilities

As it appears, ‘placed-based criminology’ has gradually development into discipline that is supported by scientific and evidence. The assumptions about the concentration of crime is evidently generalizable across different jurisdictions and the body of empirical research continues to tremendously grow. However, there are some gaps in the crime and place literature that few scholars have attempted to address. For instance, what causes crime to be highly concentrated at a small number of street segments? Or, what are the characteristics of street segments that cause crime to occur? Some of these questions have been difficult to ask because data are not often readily available at the micro-spatial level. To address these particular issues, however, crime and place research studies have primarily focused on criminological theories of opportunity to explain crime at the micro-spatial level and have largely ignored the social disorganization perspective. For instance, Sherman and colleagues (1989) argued that social disorganization theories can only be applied to community-level analysis and is inappropriate for addressing small “places with highly transient populations” (p. 30). With this, the theoretical constructs of opportunity theories can better account for the interactions between victims and offenders that occur at discrete locations because crime is dependent on the proximal circumstances within the physical environment (Weisburd et al., 2016).

Other researchers, on the other hand, have argued that street blocks and street segments have similar social processes and ecological patterns as large-scale communities (Taylor, 1997). Thus, each individual street segment in the city will have unique behaviour settings (Barker, 1968). If this proposition is accurate and street segments behave as ‘micro communities’ (Taylor, 1997), then social disorganization
theories are relevant for explaining crime at micro-places. Through rigorous analyses and extensive investigations, Weisburd, Groff and Yang (2012) were able to demonstrate that social disorganization theory does matter at the street segment level (Weisburd, Groff & Yang, 2012). Consequently, lower socioeconomic status, population turnover and ethnic heterogeneity are expected to increase the levels of crime and social disorder (Shaw & McKay, 1942). Furthermore, researchers in recent years have emphasized the importance of measuring the intervening factors of social disorganization (Sampson & Groves, 1989). This includes measuring the extent to which community members can informally organize themselves to control the actions of residents and those who pass through the community. In turn, communities with sparse friendship networks, unsupervised teenage groups and low participation in local organizations will have higher levels of crime and delinquency because of diminished capabilities of informal social control (Sampson & Groves, 1989). With respect to crime and place research, it is difficult task to operationalize these constructs at the street segment level. Data that provides information about the structural characteristics of micro-places are not often readily available because of privacy concerns or data access issues. For these reasons, scholars have neglected to consider social disorganization when studying crime at places, expect for only a handful of studies (Rice & Smith, 2000; Smith, et al., 2000; Weisburd et al., 2012). Failing to consider the constructs of social disorganization theory from future analyses, however, could potentially impose omitted variable bias onto statistical models and prevent theoretical developments in the crime and place field. (Weisburd, et al., 2012).

Although only a handful of empirical studies directly tested routine activity and social disorganization theory at micro-places, other research has shown that certain facilities increase the opportunities for criminal activity. As such, scholars found that schools (Kautt & Roncek, 2007; LaGrange, 1999; Roncek & Faggiani, 1985), shopping centres (Kinney et al., 2008; LaGrange, 1999), bars (Bernasco & Block, 2011; Roncek & Bell, 1981; Sherman et al., 1989), check-cashing centres (Kurbin et al., 2011), public housing (Fagan & Davies, 2000; Griffiths & Tita, 2009; Haberman, Groff & Taylor, 2013) and parks (Boessen & Hipp, 2018) have a positive association with crime. Furthermore, calls for police service have shown to been stable over for specific facilities in Boston: subway stations, parks, high schools and housing projects (Spelman, 1995). As a caveat, however, the analysis only included three years of data, so the results should be interpreted with caution. In another study, McCord and Ratcliffe (2007) integrated land-
use and sociodemographic variables to predict the size and location of drug markets in Philadelphia. Contrary to expectation, these facilities actually decreased the size of the drug market: drug treatment centres, liquor stores, pawn shops, homeless shelters and check-cashing stores (McCord & Ratcliffe, 2007). However, subway stations appeared to increase the size of drug markets.

In a subsequent Philadelphia study, the same researchers also found that street robberies were concentrated within a one to two block radius around subway stations (McCord & Ratcliffe, 2009). In Chicago, Bernasco and Block (2011) included a multiple facilities and illegal activities into the analysis that were expected to attract or generate criminal activity. After running the analysis, these researchers found that many of their variables had a significant and positive effect street robberies in Chicago. More recently, Haberman and Ratcliffe (2015) further investigated the relationship between robberies and criminogenic facilities at different time periods throughout the day. These researchers hypothesized that public housing, subway stations, fast-food restaurants, ATM and banks, check-cashing stores and corner stores would increase the number of street robberies at all four time periods of the day (Haberman & Ratcliffe, 2015). From the data analysis, only ATM and banks, corner stores and fast-food restaurants had increased the levels of robbery at each spatial area (Haberman & Ratcliffe, 2015). Although these studies produced empirical evidence and valuable information into the relationship between facilities and crime, none of the prior studies had used street segments as the unit of analysis.

The first set of researchers to measure the impact of certain place features/facilities on crime at micro-places was conducted by Weisburd and colleagues (2012). Expanding on the research from the original Seattle study (2004), Weisburd and colleagues (2012) extend the study period is it would be longitudinal study over sixteen years and completed another group-bases trajectory analysis. Similar to the previous studies, the analysis classified the data into different group trajectories that ranged from crime-free streets to chronic-crime streets (Weisburd et al., 2012). Furthermore, these scholars had access to multiple data files that ranged from the amount of total retail sales per street segment to the number of truant juveniles at micro-places over a sixteen-year period. (Weisburd et al., 2012). Because these researchers possessed data with such rich information, they were able to operationalize key constructs of social disorganization and routine activity theory at the street segment level. Using the results of the trajectory
analysis, these researchers utilized a multinomial logistic regression model to determine which factors would increase the likelihood of a street segment from having a chronic-crime problem compared to being crime-free (Weisburd et al., 2012). In the end, several indicators used in this study had a significant impact on crime in the theoretically expected direction.

With respect to routine activity theory and the opportunity perspective, the presence of high-risk juveniles increased the probability of a street segment to have a chronic-crime problem by twofold (Weisburd et al., 2012). This variable was intended to represent the presence of motivated offenders and had one of the largest impacts on crime. Likely representing suitable targets and business/industrial areas, the increase of the number of employees on a street segment caused the street to have a chronic crime problem by 8 percent (Weisburd et al., 2012). Further, when a public facility was located within a quarter mile radius of a street segment (e.g. middle and high school, community center, park), the odds of that street having a chronic crime problem increased by 25 percent. Additionally, streets were more likely to be grouped into the chronic crime trajectory when that street segment had a larger residential population (Weisburd et al., 2012). In terms of the urban landscape and public accessibility, bus stops, arterial roads and percentage of vacant land had significant and positive impact on predicting which streets would have a chronic-crime problem (Weisburd et al., 2012). In fact, being an arterial road had the largest impact on determining chronic crime issues, even when considering potentially confounding variables (i.e. employment and bus stops) are included in the model (Weisburd et al., 2012). Lastly, as an indicator of guardianship, street lighting on street segments actually increased the probability of having a chronic-crime problem, which is interesting because this was contrary to theory and expectation (Weisburd et al., 2012).

Turning to the social disorganization variables, these researchers found that their indicators of socioeconomic status had a strong and significant effect on street segments to have a chronic-crime problem. For instance, a one unit increase in the residential property value of a street segment decreased the odds of that street to fall in the chronic-crime category by 30 percent (Weisburd, et al., 2012). With respect to housing assistance, this variable was also a strong predictor of crime hot spots, although the effect size was not as large as property values (Weisburd et al., 2012). Being the most direct indicator of social disorganization, measures of physical disorder (i.e. graffiti, minor property
damages, abandon cars, etc.) were also found to have a positive and significant impact on street segments to be in the chronic-crime category (Weisburd et al., 2012). As for the mediating variables specified in the contemporary model of social disorganization (Sampson & Groves, 1989), the presence of unsupervised peer teenage groups (i.e. truant juveniles) increased the probability of a street segment to be a hot spot of crime (Weisburd et al., 2012). Lastly, these researchers created a variable to represent collective efficacy by using the percentage of active voters on a street segment. For instance, when all registered voters on a street segment actively voted in previous civic elections, they found that the probability of that street segment to have a chronic-crime problem actually decreased by 96 percent (Weisburd et al., 2012).

This empirical research was the most comprehensive study that investigated the causes of crime at places and attempted to operationalize key constructs from critical theories in spatial criminology. Overall, their findings support the application of routine activity and social disorganization theory at micro-spatial units of analysis. Although this seminal study was fundamental to the crime and place literature, there are further issues and unanswered questions that need to be addressed. For instance, these scholars used aggregate crime data for completing the analysis. Consequently, other researchers should determine if these results can be replicated when the analysis includes different crime types.

To address some of these issues, researchers have started to examine individual crime types and different types of crime indices. For example, Groff (2014) examined the impacts of drinking establishments on violent crime by comparing two different methodologies to measure distance exposure and incorporated several different distance thresholds into the analysis. In another study involving street segments, Groff and Lockwood (2014) separated disaggregated the data into three different crime indices: violent, property and disorder-related crimes. Furthermore, they complete the analyses at three different distance thresholds: 400 feet, 800 feet, 1200 feet (Groff & Lockwood, 2014). Controlling for different socioeconomic and demographic variables, these scholars found that nearby exposure to bars and major transit stations had a positive relationship with three crime indices at all three distance thresholds (Groff & Lockwood, 2014). Moreover, schools had a positive association with disorder-related crime at all three distance levels; halfway houses and drug treatment facilities had positive impact on various crimes at
varying distances (Groff & Lockwood, 2014). Aside from these few studies, there is very limited research in field that examines the causes of crime at micro-spatial places.

3.5. Risk Terrain Modeling

In addition to standard spatial methodology used to identify hotspots of crime, other statistical methods and spatial analyses have been developed in recent years in order to examine crime at places – risk terrain modeling (RTM). For instance, RTM was developed to be used as an analytical toolkit to identify spatial vulnerabilities and risk factors that are associated with criminal activity (Caplan & Kennedy, 2016). Unlike other criminal forecasting practices (i.e. kernel density estimation), RTM does not use historical crime data in order to predict the location of future crimes. Instead, the program operationalizes spatial risk factors to a common geography that is driven by criminological theory or any other pertinent information identified by law enforcement personnel (Caplan & Kennedy, 2010). Using a geographic information system, the software produces risk maps that are able to identify the “criminogenic and vulnerable areas at the micro-level” in order to make accurate predictions (Caplan & Kennedy, 2010). In a sense, RTM is an extension of environmental criminology, hotspot mapping, and problem-oriented policing. As the result, RTM provides police managers with actional intelligence to make operational decisions related to “tactical actions, resource allocation, and short- and long-term planning” (Caplan & Kennedy, 2010, p. 11).

In the literature, several studies have been able to produce evidence to show that this method has a certain degree of empirical validity. For starters, Caplan and colleagues (2011) apply RTM and retrospective hotspot mapping techniques to predict the locations of future illicit shootings in Irvington, New Jersey. The intention of this study was to investigate two separate issues: produce RTM maps to predict which location across the landscape have a higher risk of future shootings and determine which method is more accurate at predicting this crime type (Caplan, Kennedy & Miller, 2011). These researchers found that RTM was able to predict the location of shootings with almost 21 percent more accuracy than retrospective hotspot mapping (Caplan et al., 2011). Intended as a replication study, Kennedy and colleagues (2011) applied the same analytic strategies and methodologies as Caplan et al. (2011), but within a different city in New Jersey (Newark). However, these researchers looked at additional risk factors that might be usefully at predicting the location of shootings and compare the results to hotspot
mapping (Kennedy, Caplan & Piza, 2011). They concluded that RTM would be a useful tool for police to allocate resources more efficiently because the software is able to accurately predict which areas could potentially be problematic and have a chronic crime issue (Kennedy et al., 2011). However, these researchers argued that RTM should not replace traditional police practices, instead it used in conjunction with hotspot mapping (Kennedy et al., 2011). Lastly, in a more recent study on gun violence in Little Rock, Arkansas, Drawve and colleagues (2016) found that RTM was able to accurately predict gun related crimes with more precision than another common hotspot analysis technique – nearest neighbour hierarchical (Nnh).

In subsequent studies, Kennedy and colleagues (2016) applied the RTM framework to predict which locations are more conducive of aggravated assault in Chicago. After completing the analyses, they found that problematic buildings, nearby foreclosures and hotspots of gang activity were significant predictors of this crime type (Kennedy et al., 2016). Contrary to previous research, this crime type had a weaker connection to bars, liquor stores, and schools in Chicago (Kennedy et., 2016). Piza and colleagues (2017) utilized RTM to analyze motor vehicle theft and motor vehicle recover. In the model, the authors included variables that represented social disorganization and opportunity theories (Piza et al., 2017). To summarize, the top four risk factors were identical for both outcome variables: disorder related calls for service, foreclosures, multiple-family housing units, and hotels and motels (Piza et al., 2017). Lastly, Andresen and Hodgkinson (2018) operationalized social disorganization and routine activity theory to predict which areas have higher risk of residential burglary in Vancouver. Interestingly, the risk terrain surface maps produced results that were qualitatively different than the actual crime maps. As a result, identifying risky places with these criminological theories may not actually accurately predict the location of residential burglary within the context of Vancouver. Consequently, Andresen and Hodgkinson (2018) urge other researchers to precede with caution when applying risk factors that are specified by social disorganization and routine activity theory into the risk terrain models. As the RTM literature continues to grow, scholars are beginning to apply this method to predict different criminological phenomena and social issues. As such, RTM is being used to predict childhood maltreat (Daley et al., 2016), mafia-related homicides (Dugato, Calderoni & Berlusconi, 2017), drug dealing locations (Barnum et al., 2017), and terrorist activity (Onat, 2016). Overall, RTM is analytical technique used to operationalize criminogenic factors of
the geographic landscape and is intended to be framework within environmental criminology with practical implications for public safety operations (Caplan, 2011).

3.6. Current Study

Although several studies have investigated the criminogenic effects of certain facilities, there is limited research that examines the impact of these places on crime at street segments. Therefore, the intention of this research is to bridge some of the gaps in the crime and place literature. For instance, the previous studies aggregated the crime data in order to complete the analyses. Although this is common in the spatial crime research, disaggregating the data into individual crime types might produce different results and provide a more complete picture of the crime problem. Consequently, the aim of the current study attempts to answer the following research question: which place features have a significant impact on property crime at the street segment level?
Chapter 4.

Data and Methods

There is limited research in the crime and place literature that attempts to uncover the explanatory factors of crime at micro-places. Consequently, the purpose of this study is to address the gaps in the literature by analyzing police incident data (i.e. property crimes) and place feature data that describes the characteristics of individual street segments (i.e. facilities, place attractors, etc.). Furthermore, routine activity theory, social disorganization theory and the geometry of crime were used as a theoretical framework to guide the research process. Therefore, operational definitions were created from the theoretical constructs of each theory. In addition, the process of creating the independent variables was guided by previous empirical research. Specifically, the latest Seattle study completed by Weisburd and colleagues (2012) and the RTM literature were used as additional framework to guide the research process. This chapter will provide a detailed discussion on the data collection process, methodological issues, and the research decisions used to justify this process.

4.1. Vancouver, British Columbia – Study Setting

The City of Vancouver is geographically located in the pacific northwest region of Canada and located within the southwest region of British Columbia. Adjacent to the United States-Canada border and surrounded by the Burrard Inlet and the Fraser River, Vancouver had a recorded population of approximately 631,000 in 2016 (Statistics Canada, 2017). Further, this city falls under the Vancouver Census Metropolitan Area (CMA), which was recorded as being the third most populated metropolitan area in the country and the most populated in western Canada (Statistics Canada, 2017). The total population of the Vancouver CMA was recorded at approximately 2.5 million in 2016 and had experience a 6 percent increase in population since the last recorded census (Statistic Canada, 2017). According to the latest census, about 50 percent people living in Vancouver identify as a visible minority; therefore, this would make Vancouver the eighth most populated Canadian municipality and one of the most culturally diverse urban cities (“Population,” n.d.).
With respect to the overall patterns of crime in Vancouver, the total crime rates had decreased by 28 percent in the past ten years. From the previous year (2015), violent crime had decreased by 8 percent and property crime had increased by 1 percent. Of the three largest metropolitan area in Canada, the Vancouver CMA had the highest total crime rate (7,282 criminal code offense per 100,000 people). This was more than two times the rate of crime in Toronto (2,954 per 100,000 people) and roughly a 50 percent higher rate than Montreal (3,389 per 100,000 people). Furthermore, based off the Crime Severity Index, Vancouver has the highest value (94.3) in comparison Toronto (47.5) and Montreal - 57.8 (Keighley, 2017).

4.2. Data

The current study is a cross-sectional analysis of property crime at micro-spatial units in Vancouver in 2016. Specifically, the units of analysis are street segments (n = 13102), which are defined as two sides of a street that are between two intersections. Further, the average street length in Vancouver is approximately 119.2 meters. These data were obtained through Statistics Canada, which is an open-source dataset and available as the 2016 Census Road Network File (http://www12.statcan.gc.ca/census-recensement/2011/geo/rnf-frr/index-eng.cfm). Intersections were excluded from analysis because it is highly unlikely that these types of property crime would occur at a street intersection. If one of these crimes were to occur at an intersection, the police are more likely to record its occurrence at the nearest hundred block.

The crime data used for this study were obtained from the Vancouver Open-Data Catalogue, which can be accessed from the City of Vancouver’s official website (http://vancouver.ca/your-government/open-data-catalogue.aspx). The Vancouver Police Department (VPD) provides public access to incident report data that fall into several different crime categories. It should be noted that the data does not provide information on the total number of calls or complaints made to the VPD (e.g. calls-for-service data). For privacy concerns, there are no personal or identifying information attached to the data. Consequently, for any incident that involves an offense against a person (i.e. robbery, assault, etc.), the exact location of such offense is not provided (i.e. street name or time) and is intentionally randomized to several street blocks throughout the city. With respect to property offenses, the VPD provides information on the general location of each offense and assigns each incident to the nearest hundred-block of the street segment. For
instance, if an offense occurred at 123 Main Street, the address would be coded as 1xx Main Street. Because of this, inferences about the specific location of the criminal offense cannot be made, which is an obvious limitation to these data. However, since the analyses are completed at the street block level, the crime data will still be geocoded to the same street segment even though the exact location is not provided. Consequently, there will no be any issues pertaining to the ecological fallacy and there is limited risk of making inappropriate inferences. Specifically, the central focus of the analysis will be on the following types of property crime: residential break and enter (BNER), commercial break and enter (BNEC), theft of vehicle (TOV), theft from vehicle (TFV), and theft. For definitional purposes, if then a residential dwelling or apartment unit was burgled, then that incident would be classified as a BNER. If the building had commercial purposes or was an established business, then it the incident would be classified as a BNEC. For the motor vehicle-related offenses, a TOV incident would have to involve a stolen vehicle being reported to the police and a TFV would include any incidents where a vehicle was damaged for the purposes of stealing the material possession inside the vehicle. Lastly, in the Canadian context, theft is classified under two different categories: theft of items over $5000 and theft of items under $5000. The crime data provided by VPD aggregated these two crime types into one classification as labelled it as theft.

Next, the data used to create the independent variables to represent criminogenic facilities and place attractors were also obtained from the Vancouver Open-Data catalogue. The City of Vancouver offers public access to a variety of datasets ranging information on business licenses to the location of public washrooms and parks. As for the research process, an extensive search was conducted to find data on different facilities and place attractors that are theoretical expected to have an impact on crime or have been identify by previous studies to have an empirical association to crime (e.g. banks, bus stops, check-cashing stores, liquor stores, parks, commercial businesses, etc.). It should be noted that the information on the location of bus stops in Vancouver was obtained from the official TransLink website (https://www.translink.ca), which was also open-source and publicly available. TransLink is the corporation that is responsible for operating and maintaining public transportation service throughout the Metro Vancouver area.

A full list of the different types of facilities or place attractors that were considered for the final statistical model for each crime type are presented in table 4-1. As previously mentioned, each independent variable was intended to represent the concepts of social
disorganization theory, routine activity theory or the geometry of crime. It should be noted that the concepts of each individual theory, especially routine activity theory and the geometry of crime, are not mutually exclusive. For examples, some facilities or place features may increase the opportunities for crime because of the number of convergences between targets and offenders while also representing a crime attractor. Many of these independent variables represent crime attractors or crime generators, such as check-cashing stores, liquor stores, restaurants with and without liquor, convenience stores, retail dealers and Skytrain stations. Other variables are expected to increase the number of convergences between targets and offenders, such as banks, car parkades, restaurants, gas stations, parks, bus stops, apartments, schools, retail and secondhand dealers. Again, these two lists are not mutually exclusive and that some of these facilities could act as both a crime attractor and increase the number of convergences. Lastly, the number of streetlights present on a street segment is intended to be a measure of guardianship and is expected to have a negative relationship with crime. For example, the presence of more streetlights should deter offenders from committing crime because of the increased risk of exposure.

To clarify, secondhand dealers are defined as shops that are designated as pawn brokers, thrift stores, furniture liquidators, resellers of sports equipment, etc. As such, the Open-Data catalogue categorizes these places as retail stores that resell used goods and products. Furthermore, places such schools, community centres and parks are expected to attract a higher presence of young people. Considering that there a strong connection between youth and crime in the criminological literature, these youth place attractors are expected to increase the presence of motivated offenders; thus, increasing the amount of opportunities for criminal activity. Moreover, it should be noted that crime generators might attract specific types of criminal activity. For example, it would plausible to expect that different types of violent crime (i.e. robbery or assault) would occur near banks, check-cashing stores and liquor establishments because of the increased presence of cash carrying targets or vulnerable targets due to likelihood that these individuals would be intoxicated. Also, it would be expected that incidents of BNER would increase when there are more apartments located on a street segment because of the presence of suitable targets. This same logic would apply to street segments that have car parkades. The increase number of car parkades would increase presence of suitable targets for motor-vehicle related offense such as TOV and TFV. Although specific crime generators are
expected to have a positive impact on particular types of crime, all place attractors were placed into each model as a preliminary test. The explanation for this methodological decision will be discussed in the next section.

With respect to social disorganization theory, non-profit housing and rental units with by-law infractions are intended to be indicators of lower socioeconomic status (SES). It should also be noted that secondhand dealers are another indicator of lower SES on a street segment, especially the presence of thrift stores and pawn brokers. To elaborate, the Open-Data catalogue defines non-profit housing projects as subsidized units that are owned by government or non-profit agencies that are intended for low to moderate incomes singles and families. These buildings include social, supportive, and co-op housing; however, the list does not include single room accommodation or homeless shelters. As for rental units with by-law infractions, these buildings are defined as rental properties that have five or more by-law violations, such as electrical or building issues, problems with maintenance, untidy premise issues, etc. Consequently, this place feature was intended to represent a certain level of social disorganization that is present on a street segment. Moreover, this measure is also intended to capture the concept of population turnover from social disorganization theory. In theory, the more rental units located on a street segment will increase the rate of residents moving in and out of the neighbourhood. Thus, this will decrease the willingness of residents to intervene in order to prevent or control crime and delinquency – collective efficacy. It would also beneficial to include the number of owner-occupied dwelling units or detached housing units that are present on street segments in the analysis. However, this data was not provided in the Open-Data catalogue; this could possibly be a possible limitation to the current study that future studies could address. Furthermore, buildings that were designated as having commercial businesses and residential units were intended to be an indicator of mixed-land use. There is an expectation that communities that have multiple land use purposes are not as likely to have strong social connections among residents, as opposed to communities that only have residential units (Stark, 1987; Weisburd, 2012). Therefore, this variable intends to capture this concept from social disorganization theory.

After identifying these place attractors or criminogenic facilities, these places were mapped onto the corresponding street segments by the process of reverse geocoding. This process was possible because the x- and y- coordinates were available in the datasets. Similar procedures were conducted for the crime data. After the crime and place
4.3. Methods

The analytic process for this research project was conducted in various stages. First, there was a decision to determine which statistical model would be most appropriate for analysis based on certain assumptions and the inherent nature of the data. For instances, both crime variables were highly skewed in the positive direction and represented a reverse ‘J’ curve (see figure 4-1). This distribution is not surprising since other researchers have identified these spatial patterns within the context of Vancouver (Andresen & Malleson, 2011; Andresen et al., 2017; Curman et al., 2015). Considering these factors, a count data model would be most suitable for this project. An ordinary least squares (OLS) regression model could have been used in the context of the current analyses, however this method would produce parameter estimates that are less efficient. Second, depending on the type of regression model that was being tested (i.e. Poisson or negative binominal), all place attractor variables were placed into the model. After that, the model was tested down to assess omitted variable bias. The reason for including all place attractors initially into the model was a methodological strategy to ensure that relevant spatial factors were included in the models and were not susceptible to omitted variable bias. For instance, although car parkades are not theoretically expected to increase BNER, important information about certain place features might potentially go undetected if those places features were left out of the model. In order to assess omitted variable bias, therefore, the variables with the highest p-value were removed in sequential order. Next, a joint significance test was conducted between the full and final model to determine if removing those variables with the highest p-value had changed the model significantly. Similarly, these methods were also conducted by removing the variables with the lowest p-value. Table 4.1 lists all variables that were tested in the initial stages of implementing this modeling strategy.

To begin the analyses, a Poisson model was used to analyze all five property crimes. As mentioned previously, every place attractor variable was put into the model to test for potential omitted variable bias. After testing down the model, the dispersion test was applied to the final model. Because the statistic for the dispersion test exceed the threshold of statistical significance (p < 0.05), the null hypothesis was rejected that the
data were not overdispersed. In other words, the variance was not equal to the mean and the data were overdispersed for all crime types. For these reasons, a negative binomial regression model would be more suitable than a Poisson model for these data. Again, the model was tested down within the context of negative binomial regression for both crime types.
Furthermore, there were other considerations that needed to be addressed. For instance, a decision had to be made to determine if a zero-inflated negative binomial regression model (ZINB) would actually be more appropriate for the data than a regular negative binominal model. For the theft model, would a zero-inflated Poisson model be appropriate because of the distribution of the data. On the surface, it makes logical sense to account for the zeros because roughly 80 and 90 percent of the street segments in

**Figure 4-1  Distribution of Property Crimes Used for Analysis**
Vancouver did not have an incident of BNER and BNEC, respectively. In terms of the motor-vehicle related crimes, TOV had similar patterns for the zero counts on street segments (91 percent), although TFV was a bit more dispersed and the zero counts were located on over half of the street segments in the city (66.5 percent). Lastly, the overwhelming majority of street segments in Vancouver did not have an incident of theft (96.5 percent).

**Table 4-1  Place Attractors / Features**

<table>
<thead>
<tr>
<th>Place Attractors / Features</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>Restaurants with liquor</td>
</tr>
<tr>
<td>Car parkades</td>
<td>Restaurants without liquor</td>
</tr>
<tr>
<td>Check-cashing stores</td>
<td>Apartments</td>
</tr>
<tr>
<td>Community centres</td>
<td>Bus stops</td>
</tr>
<tr>
<td>Convenience stores</td>
<td>Rental units (By-law issues)</td>
</tr>
<tr>
<td>Gas stations</td>
<td>Residential/commercial</td>
</tr>
<tr>
<td>Liquor stores</td>
<td>Retail dealers</td>
</tr>
<tr>
<td>Non-profit housing</td>
<td>Secondhand dealers</td>
</tr>
<tr>
<td>Parks</td>
<td>Skytrain stations</td>
</tr>
<tr>
<td>Schools</td>
<td>Streetlights</td>
</tr>
</tbody>
</table>

Furthermore, the possibility of having a zero count on a street segment can be explained by two potential scenarios. For example, a street segment that only consists of residential units cannot have an incident of BNEC because there are no commercial businesses to victimize. Also, there will be street segments that do have commercial businesses but do not have any incidents of BNEC. This same logical reasoning can also be applied to BNER; this offense can only occur on street segments that only have residential buildings. In other words, there is an expectation that the zero outcome has two different data generating processes. Furthermore, this logic reason can also be applied to both motor vehicle-related offenses. For example, some streets will have no parked vehicles to victimize because of parking restrictions; therefore, these streets will never have an incident of TOV or TFV. However, this logical reasoning does not apply to incidents of theft. Although, these are just some explanations of why a zero-inflated model is better for this dataset, although there needs to be more justifications that is based on statistical evidence.
At a statistical level, multiple variables appeared significant in the logit model after running the zero-inflated models for all crime types. Because of these results, it shows that the model does well for predicting the excess zeros; this would be a slight indication that the zero-inflated model would be a better choice for this dataset. Additionally, the zero-inflated models had lower AIC scores in comparison to the regular negative binomial models; this would be another indication that the ZINB models are a better fit for the data (see table 4-2). Lastly, the Vuong test was used to compare the results of the ZINB models and the regular negative binominal models.

<table>
<thead>
<tr>
<th>Table 4-2</th>
<th>AIC Scores for Crime Types</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BNER</td>
</tr>
<tr>
<td>Negative Binomial</td>
<td>14,657.14</td>
</tr>
<tr>
<td>Zero-Inflated Negative Binomial</td>
<td>14,228.17</td>
</tr>
</tbody>
</table>

The results of the Voung test reached the threshold of statistical significance (p < 0.05); therefore, this test demonstrated that the ZINB model is a significant improvement from the regular negative binominal model because the null hypothesis was rejected. Based on statistical evidence and face validity, these are the justifications for applying the ZINB model instead of a regular count model.

To conclude the initial data inspection, potential issues of multicollinearity were assessed with respect to the final model. It should be noted that the author was not aware of any R code that could check for multicollinearity within the context of zero inflated models. Although there was no obvious solution to this problem, multicollinearity was measured in a regular negative binominal model with the same variables that were used in the final zero-inflated model for all crime types. As a result, none of the variable had a VIF value of 5 or over; therefore, multicollinearity is not expected to be an issue with these data.

4.4. Descriptive Results

The descriptive statistics for all five crime types are presented in table 4-3. The first column is the total counts of place features (or crimes) that are present throughout the entire city. As expected, the mean values for both crime types are very low. Because an overwhelming number of street segments have zero counts for both types of variables,
it was expected that the mean scores would be very low. For instance, roughly 17 and 9 percent of street segments had at least incident of BNER or BNEC, respectively. In other words, the overwhelming majority of these street segments had zero incidents of either crime type. For the motor vehicle related offenses, roughly 33 and 9 percent of the streets have at least one incident of TFV and TOV, respectively. Lastly, roughly 4 percent of the street segments have at least one incident of theft.

Table 4-3  Descriptive Statistics – Property Crime

<table>
<thead>
<tr>
<th></th>
<th>Count (n)</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNER</td>
<td>2,140</td>
<td>0.23</td>
<td>0.00</td>
<td>8.00</td>
<td>0.60</td>
</tr>
<tr>
<td>BNEC</td>
<td>2,689</td>
<td>0.21</td>
<td>0.00</td>
<td>23.00</td>
<td>0.90</td>
</tr>
<tr>
<td>TOV</td>
<td>1,972</td>
<td>0.11</td>
<td>0.00</td>
<td>6.00</td>
<td>0.40</td>
</tr>
<tr>
<td>TFV</td>
<td>12,372</td>
<td>0.98</td>
<td>0.00</td>
<td>116.00</td>
<td>3.90</td>
</tr>
<tr>
<td>THEFT</td>
<td>13,475</td>
<td>0.44</td>
<td>0.00</td>
<td>276.00</td>
<td>6.22</td>
</tr>
</tbody>
</table>

Moreover, the mean scores for BNER and BNEC were almost identical, although the mean count is slightly larger for BNER. TFV had the highest mean score out of all five property crime types. With respect to total counts, theft (n = 13,475) was the most frequently occurring property crime in the city and TOV (n = 1,972) was the least frequent offense in Vancouver. Although, it should be noted that TFV (n = 12,372) also had a high occurrence throughout the city, and BNER (n = 2,140) and BNEC (n = 2,689) had very similar total counts throughout the city. Furthermore, the fourth and fifth column describe the maximum and minimum number of counts of a place or crime that could occur on a street segment. For example, the maximum number of BNEC to occur on a street segment was 23. This value was much larger than the maximum value for BNER (8). Theft had the highest maximum value; one of the street segments in Vancouver had a total of 276 incidents of theft reported to the police. The second largest maximum value was TFV; one of the street segments had a total of 116 recorded incidents. Lastly, three street segments had a total of 6 incidents of TOV reported to the police.
Table 4-4  Descriptive Statistics – Place Attractors

<table>
<thead>
<tr>
<th>Place Attractors</th>
<th>Count (n)</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>144</td>
<td>0.01</td>
<td>0.00</td>
<td>4.00</td>
<td>0.14</td>
</tr>
<tr>
<td>Car parkades</td>
<td>318</td>
<td>0.02</td>
<td>0.00</td>
<td>4.00</td>
<td>0.19</td>
</tr>
<tr>
<td>Check-cashing stores</td>
<td>41</td>
<td>0.00</td>
<td>0.00</td>
<td>3.00</td>
<td>0.07</td>
</tr>
<tr>
<td>Community centres</td>
<td>27</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.05</td>
</tr>
<tr>
<td>Convenience stores</td>
<td>278</td>
<td>0.02</td>
<td>0.00</td>
<td>4.00</td>
<td>0.17</td>
</tr>
<tr>
<td>Gas stations</td>
<td>77</td>
<td>0.01</td>
<td>0.00</td>
<td>1.00</td>
<td>0.08</td>
</tr>
<tr>
<td>Liquor stores</td>
<td>100</td>
<td>0.01</td>
<td>0.00</td>
<td>3.00</td>
<td>0.10</td>
</tr>
<tr>
<td>Non-profit housing</td>
<td>232</td>
<td>0.02</td>
<td>0.00</td>
<td>5.00</td>
<td>0.17</td>
</tr>
<tr>
<td>Parks</td>
<td>222</td>
<td>0.02</td>
<td>0.00</td>
<td>2.00</td>
<td>0.13</td>
</tr>
<tr>
<td>Restaurants (Liquor)</td>
<td>1,225</td>
<td>0.09</td>
<td>0.00</td>
<td>11.00</td>
<td>0.54</td>
</tr>
<tr>
<td>Restaurants (No Liquor)</td>
<td>561</td>
<td>0.04</td>
<td>0.00</td>
<td>5.00</td>
<td>0.27</td>
</tr>
<tr>
<td>Schools</td>
<td>113</td>
<td>0.01</td>
<td>0.00</td>
<td>2.00</td>
<td>0.10</td>
</tr>
<tr>
<td>Apartments</td>
<td>2,746</td>
<td>0.24</td>
<td>0.00</td>
<td>32.00</td>
<td>1.09</td>
</tr>
<tr>
<td>Bus stops</td>
<td>1,790</td>
<td>0.14</td>
<td>0.00</td>
<td>6.00</td>
<td>0.45</td>
</tr>
<tr>
<td>Rental units (By-law)</td>
<td>372</td>
<td>0.03</td>
<td>0.00</td>
<td>5.00</td>
<td>0.21</td>
</tr>
<tr>
<td>Residential / commercial</td>
<td>232</td>
<td>0.02</td>
<td>0.00</td>
<td>5.00</td>
<td>0.15</td>
</tr>
<tr>
<td>Retail dealers</td>
<td>136</td>
<td>0.21</td>
<td>0.00</td>
<td>73.00</td>
<td>1.34</td>
</tr>
<tr>
<td>Secondhand dealers</td>
<td>3,135</td>
<td>0.01</td>
<td>0.00</td>
<td>4.00</td>
<td>0.12</td>
</tr>
<tr>
<td>Skytrain stations</td>
<td>22</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.04</td>
</tr>
<tr>
<td>Streetlights</td>
<td>56,042</td>
<td>4.28</td>
<td>0.00</td>
<td>115.00</td>
<td>4.14</td>
</tr>
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</table>

With respect to the independent variables, the total number of place attractors throughout the city had a large variation, which is report in the second column of table 4-4. For example, on the low-end of the scale, there were only twenty-seven community centres across the city. On the high-end of the scale, there were over 56,000 streetlights. Most place attractors had a fairly low maximum value that ranged from 1 to 4. This is not surprising since it is unlikely that a street segment will have more than one school or more than one community centre. On the other hand, some place attractors had higher maximum value at street segments, such as apartment buildings, retail stores, and restaurants with liquor. This is not too surprising also because there will be commercial areas with street segment that will only have retail stores, and there will be residential areas that have a high number of apartment buildings on street segments.
4.5. Bivariate Correlations – Independent Variables

Table 4 displays the measures of association between independent variables used for analysis. Because the data are not normally distributed, Spearman’s Rho was used to measure the correlations. As shown in table 4, many of these associations have a significance value of less than 0.05. Furthermore, these significant correlations were either weak or very weak in the positive direction. The relationships that are worth mentioning is the association that retail stores have with restaurants with liquor ($Rho = 0.45; p < 0.05$) and restaurants without liquor ($Rho = 0.36; p < 0.05$). Also, noteworthy is the association that banks have with restaurants with liquor ($Rho = 0.30; p < 0.05$) and restaurants without liquor ($Rho = 0.30; p < 0.05$). Lastly, there is a moderate relationship between restaurants with liquor and restaurants without liquor ($Rho = 0.41; p < 0.05$), and there is also a moderate relationship between convenience stores and gas stations ($Rho = 0.01; p < 0.05$). None of the correlation coefficients had a value that was even close to 0.80, which is used as a common threshold for concerns of multicollinearity.
Table 4-5  Correlations Coefficients for Independent Variables used in the Count Data Models (Spearman’s Rho)

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<th></th>
<th>X_1</th>
<th>X_2</th>
<th>X_3</th>
<th>X_4</th>
<th>X_5</th>
<th>X_6</th>
<th>X_7</th>
<th>X_8</th>
<th>X_9</th>
<th>X_10</th>
<th>X_11</th>
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<th>X_15</th>
<th>X_16</th>
<th>X_17</th>
<th>X_18</th>
<th>X_19</th>
<th>X_20</th>
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<tr>
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<td>0.19*</td>
<td>0.12*</td>
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<td>0.02*</td>
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<td>0.05*</td>
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<td>0.02*</td>
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<td>0.08*</td>
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<td>0.10*</td>
<td>0.06*</td>
<td>-0.01</td>
<td>0.24*</td>
<td>0.16*</td>
<td>-0.01</td>
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<td>0.08*</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.04*</td>
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<td>0.00</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.09*</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.02*</td>
<td>0.02</td>
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<td>X_20</td>
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<td>0.14*</td>
<td>0.05*</td>
<td>0.03*</td>
<td>0.14*</td>
<td>0.08*</td>
<td>0.07*</td>
<td>0.08*</td>
<td>0.07*</td>
<td>0.21*</td>
<td>0.18*</td>
<td>0.04*</td>
<td>0.20*</td>
<td>0.29*</td>
<td>0.11*</td>
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<td>0.25*</td>
<td>0.10*</td>
<td>0.02*</td>
<td>1.00</td>
</tr>
</tbody>
</table>

* p < 0.05

X_1: banks; X_2: car parkades; X_3: check-cashing stores; X_4: community centres; X_5: convenience stores; X_6: gas stations; X_7: liquor stores; X_8: non-profit housing; X_9: parks; X_{10}: restaurants (Liquor); X_{11}: restaurants (no liquor); X_{12}: school; X_{13}: apartments; X_{14}: bus stops; X_{15}: rental units (by-laws); X_{16}: residential/commercial; X_{17}: retail dealers; X_{18}: secondhand dealers; X_{19}: Skytrain stations; X_{20}: streetlights

Note: Correlations with a value of (0.00) do not indicate a completely absent relationship. Because the values were rounded to the nearest hundredth decimal place, a value of (0.00) would indicate a very weak positive or negative relationship.
Chapter 5.

Results

Next, the relationship between BNER/BNEC and place attractors were tested at the multivariate level using zero-inflated negative binominal models. As demonstrated in the tables, the raw parameter estimates are presented for each independent variable. However, these beta scores are more difficult to interpret; therefore, these estimates were then converted into an incident rate ratio (IRR) for easier interpretations. For example, an IRR value of 2.0 would indicate that a one unit increase in the number of car parkades on a street segment would increase the count of the dependent variable by 100%. In contrast, an IRR value of 0.5 would indicate that a one-unit increase in the independent variable would decrease the count of the dependent variable by 50%.

5.1. Residential Break and Enter

To begin, the results of BNER will be interpreted first (see Table 5-1). In the logit model, several variables emerged as having a significant impact on predicting the excess zeros for BNER on street segments. Consequently, the model is making prediction on which places will constantly have zero counts of BNER. For example, gas stations had the largest estimate in the positive direction \(b = 4.70; p < .001\). In other words, a one unit increase in the number of gas stations on a street segment increases the likelihood that a street segment will experience zero incidents of BNER. Furthermore, check-cashing stores had the second largest estimate in the positive direction for predicting the excess zeros \(b = 3.28; p < .05\). Thus, a one unit increase in the number of check-cashing stores on a street segment will increase the likelihood of having a zero count of BNER. The same interpretations can be applied to the following facilities in the logit model: car parkades \(b = 1.63; p < .01\), second-hand dealers \(b = 2.76; p < .05\), and bus stops \(b = 0.66; p < .05\) – these facilities are listed in rank-order from largest to smallest parameter estimates. Although several variables were significant and positive in the logit model, only two facilities were significant and negative. For instance, a one unit increase in the number of apartments on a street segment will decrease the likelihood that a street will experience a zero count of BNER \(b = -1.09; p < .01\). Further, a one unit increase in the number of streetlights on a street segment will decrease the likelihood of having a zero count of
BNER ($b = -0.77; p < .001$). Based on these interpretations, it is expected that apartments and streetlights will be positive in the count model since these variables have negative relationship with BNER for predicting the excess zeros. On the opposite side, the positive variables in the logit model are expected to be negative in the count model.

Table 5-1    Zero-Inflated Negative Binomial Regression (BNER)

<table>
<thead>
<tr>
<th></th>
<th>Logit model</th>
<th></th>
<th>Count model</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$b$</td>
<td>SE</td>
<td>OR</td>
<td>$b$</td>
</tr>
<tr>
<td>Car parkades</td>
<td>1.63</td>
<td>0.55</td>
<td>5.08 **</td>
<td>-0.05</td>
</tr>
<tr>
<td>Check-cashing stores</td>
<td>3.28</td>
<td>1.35</td>
<td>26.56 *</td>
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<td>Community centres</td>
<td>-6.85</td>
<td>45.92</td>
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<tr>
<td>Convenience stores</td>
<td>-0.45</td>
<td>0.83</td>
<td>0.64</td>
<td>-0.13</td>
</tr>
<tr>
<td>Gas stations</td>
<td>4.70</td>
<td>1.06</td>
<td>110.24 ***</td>
<td>0.32</td>
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<tr>
<td>Liquor stores</td>
<td>-4.26</td>
<td>4.03</td>
<td>0.01</td>
<td>-0.13</td>
</tr>
<tr>
<td>Non-profit housing</td>
<td>-0.30</td>
<td>1.24</td>
<td>0.74</td>
<td>0.42</td>
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<tr>
<td>Parks</td>
<td>-0.57</td>
<td>0.87</td>
<td>0.57</td>
<td>-0.11</td>
</tr>
<tr>
<td>Restaurants (Liquor)</td>
<td>0.10</td>
<td>0.30</td>
<td>1.11</td>
<td>-0.06</td>
</tr>
<tr>
<td>Restaurants (No Liquor)</td>
<td>-1.08</td>
<td>0.94</td>
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<td>-0.21</td>
</tr>
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<td>Schools</td>
<td>-0.68</td>
<td>1.11</td>
<td>0.50</td>
<td>0.28</td>
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<tr>
<td>Apartments</td>
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<td>0.37</td>
<td>0.34 **</td>
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<td>Bus stops</td>
<td>0.66</td>
<td>0.27</td>
<td>1.93 *</td>
<td>-0.22</td>
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<td>Rental units (By-law)</td>
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<td>Retail dealers</td>
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<td>0.06</td>
<td>1.08</td>
<td>0.03</td>
</tr>
<tr>
<td>Secondhand dealers</td>
<td>2.76</td>
<td>1.13</td>
<td>15.79 *</td>
<td>-0.04</td>
</tr>
<tr>
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<td>-0.77</td>
<td>0.06</td>
<td>0.46 ***</td>
<td>0.03</td>
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<tr>
<td>(Intercept)</td>
<td>2.09</td>
<td>0.12</td>
<td>8.12 ***</td>
<td>-1.17</td>
</tr>
</tbody>
</table>

Goodness-of-fit (AIC) 14,228.17

Abbreviations: $b =$ unstandardized coefficients; SE = standard error; OR = odds ratio; IRR = incident risk ratio
+p < .10; *p < .05; **p < .01; ***p < .001

The count model is estimating which place features have a significant impact on predicting the counts of BNER. As demonstrated in the third column of table 5-1, only portions of the count model were consistent with some of those expectations that were previously mentioned. For instance, there was a sign switch for apartments ($b = 0.05; p < .01$), streetlights ($b = 0.03; p < .001$), and bus stops ($b = -0.22; p < .001$) in the count model. Of these variables, bus stops appeared to have the strongest influence, as a one unit increase in the number of bus stops on street segment decreases the rate of expected counts of BNER by 20 percent. Streetlights and apartments did not appear to be have as
large of an impact as bus stops on BNER. These facilities only increase the expected rate of BNER on a street segment by roughly 3 and 5 percent, respectively.

Other than those facilities that were previously mentioned, the other variables that were significant in the logit model are no longer significant in the count model. Furthermore, new variables emerged as having a significant impact on predicting the counts of BNER. For example, non-profit housing units had the largest estimates in the positive direction ($b = 0.42; p < .001$). In other words, a one-unit increase in the number of non-profit housing units increases the rate of expected BNER by 52 percent. Restaurants without liquor had similar estimates as bus stops ($b = -0.21; p < .05$). Thus, a one unit increase of the number of restaurants without liquor on a street segment decreases the rate of expected BNER by 19 percent. Lastly, rental units with by-law infractions ($b = 0.13; p < .10$) and retail businesses ($b = 0.03; p < .10$) had a positive effect on increasing the number of incidents of BNER on a street segment. However, it should be noted that these variables are marginally significant ($p < .10$). To elaborate, a one-unit increase in the number of rental units and retail dealers is associated with an increase in BNER on a street segment by 14 and 3 percent, respectively.

### 5.2. Commercial Break and Enter

With respect to BNEC, the results for the logit and count model are presented in table 5-2. Starting with the logit model, multiple variables had a significant impact on predicting the excess zero counts of BNEC on street segments. In addition, these significant variables all have a negative relationship with this crime type; therefore, these facilities have a negative impact on predicting the excess zero counts of BNEC. Just like in the previous zero-inflated model, these facilities are expected to have a positive and significant effect in the count model. For the purposes of interpretation, these places are statistically significant: car parkades ($b = -3.63; p < .05$), parks ($b = -0.87; p < .10$), restaurants with liquor ($b = -1.97; p < .001$), restaurants without liquor ($b = -2.09; p < .01$), schools ($b = -1.87; p < .05$), apartments ($b = -1.16; p < .001$), bus stops ($b = -0.64; p < .001$), rental units with by-law issues ($b = -1.49; p < .05$), retail dealers ($b = -1.11; p < .001$) and streetlights ($b = -0.03; p < .05$). With respect to rank order, car parkades had the largest parameter estimate for predicting the counts of zero. Restaurants without liquor had the second largest estimate, restaurants with liquor had the third largest estimate, and schools had the fourth largest estimate.
Next, the results of the count model for BNEC are presented in the last column of Table 4. Unlike the previous model for BNER, only a few variables that were significant in the logit model and non-significant in the count model: restaurants without liquor and rental units (by-law issues). On the other hand, non-profiting housing units ($b = 0.26; p < .05$) are significant in the count model but were non-significant in the logit model. For instance, a one-unit increase in the number of non-profit houses increases the rate of expected BNEC on a street segment by 30 percent, which is the third largest parameter estimate in the count model. Furthermore, the other significant variables in the logit model remained significant and switched signs in the count model. Interestingly, parks ($b = -0.91; p < .001$) and schools ($b = -0.85; p < .05$) continued to be significant and negative in the count model. Consequently, these facilities have a negative impact on predicting the counts of BNEC on street segments and have the largest parameter estimates.

![Table 5-2: Zero-Inflated Negative Binomial Regression (BNEC)](image-url)

<table>
<thead>
<tr>
<th></th>
<th>Logit model</th>
<th>Count model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b$</td>
<td>SE</td>
</tr>
<tr>
<td>Car parkades</td>
<td>-3.63</td>
<td>1.56</td>
</tr>
<tr>
<td>Check-cashing stores</td>
<td>1.51</td>
<td>1.11</td>
</tr>
<tr>
<td>Community centres</td>
<td>-1.53</td>
<td>1.31</td>
</tr>
<tr>
<td>Convenience stores</td>
<td>0.21</td>
<td>0.62</td>
</tr>
<tr>
<td>Gas stations</td>
<td>0.24</td>
<td>1.04</td>
</tr>
<tr>
<td>Liquor stores</td>
<td>-15.21</td>
<td>1252.97</td>
</tr>
<tr>
<td>Non-profit housing</td>
<td>-0.80</td>
<td>0.84</td>
</tr>
<tr>
<td>Parks</td>
<td>-0.87</td>
<td>0.50</td>
</tr>
<tr>
<td>Restaurants (Liquor)</td>
<td>-1.97</td>
<td>0.59</td>
</tr>
<tr>
<td>Restaurants (No Liquor)</td>
<td>-2.09</td>
<td>0.67</td>
</tr>
<tr>
<td>Schools</td>
<td>-1.87</td>
<td>0.94</td>
</tr>
<tr>
<td>Apartments</td>
<td>-1.16</td>
<td>0.16</td>
</tr>
<tr>
<td>Bus stops</td>
<td>-0.64</td>
<td>0.12</td>
</tr>
<tr>
<td>Rental units (By-law)</td>
<td>-1.49</td>
<td>0.68</td>
</tr>
<tr>
<td>Retail dealers</td>
<td>-1.11</td>
<td>0.18</td>
</tr>
<tr>
<td>Secondhand dealers</td>
<td>-1.29</td>
<td>1.06</td>
</tr>
<tr>
<td>Streetlights</td>
<td>-0.03</td>
<td>0.01</td>
</tr>
</tbody>
</table>

(Intercept) 2.03 0.10 7.65 *** -1.00 0.09 0.37 ***

Goodness-of-fit (AIC) 9,893.45

Abbreviations: $b =$ unstandardized coefficients; SE = standard error; OR = odds ratio; IRR = incident risk ratio
*p < .10; *p < .05; **p < .01; ***p < .001
example, a one-unit increase in the number of parks or schools on a street segment decreases the rate of expected BNEC by 60 and 57 percent, respectively.

In the positive direction, car parkades \((b = 0.22; p < .01)\) also had a notable impact on the rate of BNEC; a one-unit increase in the number of parkades increases the rate of expected BNEC on a street segment by 24 percent. Regarding other places, these are the remaining significant variables in the count model: restaurants with liquor \((b = 0.12; p < .001)\), apartments \((b = 0.04; p < .01)\), bus stops \((b = 0.14; p < .05)\), retail dealers \((b = 0.03; p < .10)\) and streetlights \((b = 0.08; p < .001)\). Notably, a one-unit increase in the number of restaurants with liquor increase the rate of expected BNEC by 13 percent. Further, a one-unit increase in the number of bus stops on a street segment increase the rate of expected BNEC by 15 percent. Comparatively, the effect of apartments, retail dealers and streetlights on BNEC are rather small. It is interesting how some variables had a significant relationship in the logit model, but not in the count model. On the other side, some variables were significant in the count model, but not in the logit model. These findings contradict the intuitive logic behind zero-inflated models and would require further investigation.

5.3. Theft of Vehicle

Turning to the results for theft of vehicle (TOV), only a small number of variables emerged as being significant in the logit model (table 5-3). Presented in rank-order from largest to smallest coefficients, these place attractors had a negative impact on predicting the excess zeros: apartments \((b = -2.44; p < .01)\); retail dealers \((b = -0.97; p < .05)\), and streetlights \((b = -0.40; p < .001)\). In the positive direction, banks \((b = 4.24; p < .05)\) had a positive effect on predicting the excess zeros. Moving to the count model, several variables had a significant effect on predicting the counts of TOV. For example, Non-profit housing \((b = 0.56)\) and apartment units \((b = 0.07)\) were significant at the statistical threshold of less than .001 and had a positive effect on predicting the counts of TOV. Specifically, a one-unit increase in the number of non-profit housing and apartment units increases the rate of expected TOV by 75 and 7 percent, respectively. At the .01 statistical significance threshold, rental units with by-law infractions \((b = 0.25)\) and streetlight \((b = 0.02)\) have a positive impact on predicting the excess counts of TOV. As such, rental units and streetlights increase the rate of expected TOV by 28 and 2 percent, respectively. On the other hand, bus stops \((b = -0.20)\) actually have a negative impact on predicting the
counts and decrease the rate of expect TOV by 18 percent. Lastly, car parkades ($b = 0.27$; $p < 0.05$) had a significant and positive effect on TOV at the threshold of less than .05. With respect to the magnitude, non-profit housing has the largest coefficient and street streetlights has the smallest coefficient.

Table 5-3  Zero-Inflated Negative Binomial Regression (TOV)

| Logit model | Count model |
|-------------|-------------|-------------|-------------|-------------|
|             | $b$  | SE  | OR  | $b$  | SE  | IRR |
| Banks       | 4.24 | 2.01 | 69.56 | * | 0.27 | 0.18 | 1.31 |
| Car parkades| -1.07 | 2.05 | 0.34 | 0.24 | 0.10 | 1.27 | * |
| Check-cashing stores | 4.61 | 3.09 | 100.26 | -0.38 | 0.44 | 0.68 |
| Community centres | -10.92 | 130.43 | 0.00 | 0.48 | 0.37 | 1.62 |
| Convenience stores | -0.01 | 0.93 | 0.99 | 0.08 | 0.13 | 0.92 |
| Gas stations | 2.20 | 1.50 | 9.05 | 0.15 | 0.43 | 1.08 |
| Liquor stores | -16.77 | 21.94 | 0.00 | -0.01 | 0.20 | 0.99 |
| Non-profit housing | 0.26 | 0.34 | 1.29 | 0.56 | 0.10 | 1.75 | *** |
| Parks | -0.67 | 0.88 | 0.51 | -0.10 | 0.22 | 0.90 |
| Restaurants (Liquor) | -0.88 | 0.72 | 0.42 | 0.05 | 0.04 | 1.05 |
| Restaurants (No Liquor) | -0.47 | 1.18 | 0.62 | 0.03 | 0.09 | 1.03 |
| Schools | -1.86 | 3.55 | 0.16 | -0.74 | 0.49 | 0.48 |
| Apartments | -2.44 | 0.91 | 0.09 | ** | 0.07 | 0.02 | 1.07 | *** |
| Bus stops | 0.26 | 0.24 | 1.30 | -0.20 | 0.07 | 0.82 | ** |
| Rental units (By-law) | 0.04 | 0.51 | 1.04 | 0.25 | 0.08 | 1.28 | ** |
| Retail dealers | -0.97 | 0.42 | 0.38 | * | 0.01 | 0.01 | 1.01 |
| Streetlights | -0.40 | 0.05 | 0.67 | *** | 0.02 | 0.01 | 1.02 | ** |
| (Intercept) | 1.78 | 0.15 | 5.92 | *** | -1.70 | 0.10 | 0.18 | *** |
| Goodness-of-Fit (AIC) | 8,691.25 | |

Abbreviations: $b =$ unstandardized coefficients; SE = standard error; OR = odds ratio; IRR = incident risk ratio
*p < .10; *p < .05; **p < .01; ***p < .001

5.4. Theft from Vehicle

With respect to TFV, only three variables had a significant relationship in the logit model (table 5-4). For instance, apartments ($b = -2.91$; $p < .05$) and streetlights ($b = -0.68$; $p < .001$) have a negative effect on predicting the excess zeros, and these variables are expected to have positive coefficients in the count model. On the other hand, bus stop ($b = 0.96$; $p < 0.001$) have a positive effect on predicting the excess zero counts of TFV on a street segment and are expected to have a negative coefficient in the count model.
In the count model, more than half of the place attractors had a significant relationship with this crime type. Of the significant variables in the count model, eight place attractors had a positive impact at predicting the counts of TFV at street segments. Therefore, the presence of these facilities on a street segment would increase the probability on an incident of TFV to occur: car parkades \((b = 0.91; p < 0.001)\), convenience stores \((b = 0.46; p < 0.001)\), non-profiting housing units \((b = 0.50; p < 0.001)\), restaurants with a liquor license \((b = 0.20; p < 0.001)\), apartment buildings \((b = 0.15; p < 0.001)\), retail dealers \((b = 0.04; p < 0.01)\), Skytrain stations \((b = 1.06; p < 0.01)\), and streetlights \((\beta = 0.07; p < 0.001)\). In terms of the larger coefficient, the presence of car parkades and Skytrain stations on a street segment increase the expected rate of TFV by 188 and 149 percent, respectively. In terms of the smaller coefficients, retail dealers and streetlights increase the rate of expected TFV by 4 and 8 percent, respectively.

In the opposite direction, these variables have a negative impact on predicting the counts of TFV on street segment. For example, gas stations \((b = -0.57; p < 0.01)\), buildings with commercial and residential purposes \((b = -0.23; p < 0.05)\), secondhand stores \((b = -0.24; p < 0.10)\) and bus stops \((b = -0.07; p < 0.10)\) are expected to decrease the rate of expected TFV on a street segment. However, it should be noted that secondhand stores and bus stops are only marginally significant at a statistical threshold of less than .10. In terms of rank-order, gas stations have the largest effect on decreasing the expected rate of TFV (43 percent), commercial/residential buildings and secondhand stores roughly have similar effect sizes (21 percent), and bus stops have the smallest effect on decreasing the expected rate of TFV on a street segment (7 percent).
Table 5-4. Zero-Inflated Negative Binomial Regression (TFV)

<table>
<thead>
<tr>
<th>Place Attractors</th>
<th>Logit model</th>
<th>Count model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b$</td>
<td>SE</td>
</tr>
<tr>
<td>Banks</td>
<td>-0.85</td>
<td>1.90</td>
</tr>
<tr>
<td>Car parkades</td>
<td>-1.28</td>
<td>2.00</td>
</tr>
<tr>
<td>Check-cashing stores</td>
<td>-0.62</td>
<td>2.85</td>
</tr>
<tr>
<td>Community centres</td>
<td>0.81</td>
<td>1.60</td>
</tr>
<tr>
<td>Convenience stores</td>
<td>0.91</td>
<td>1.18</td>
</tr>
<tr>
<td>Gas stations</td>
<td>-0.50</td>
<td>1.66</td>
</tr>
<tr>
<td>Liquor stores</td>
<td>-0.89</td>
<td>4.92</td>
</tr>
<tr>
<td>Non-profit housing</td>
<td>-1.24</td>
<td>1.05</td>
</tr>
<tr>
<td>Parks</td>
<td>-1.29</td>
<td>1.04</td>
</tr>
<tr>
<td>Restaurants (Liquor)</td>
<td>-3.45</td>
<td>4.51</td>
</tr>
<tr>
<td>Restaurants (No Liquor)</td>
<td>-0.61</td>
<td>2.32</td>
</tr>
<tr>
<td>Apartments</td>
<td>-2.91</td>
<td>1.24</td>
</tr>
<tr>
<td>Bus stops</td>
<td>0.96</td>
<td>0.19</td>
</tr>
<tr>
<td>Residential / commercial</td>
<td>-7.28</td>
<td>32.64</td>
</tr>
<tr>
<td>Retail dealers</td>
<td>-1.48</td>
<td>0.95</td>
</tr>
<tr>
<td>Skytrain stations</td>
<td>-1.38</td>
<td>1.33</td>
</tr>
<tr>
<td>Secondhand dealers</td>
<td>-7.52</td>
<td>35.36</td>
</tr>
<tr>
<td>Streetlights</td>
<td>-0.68</td>
<td>0.05</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.13</td>
<td>0.09</td>
</tr>
<tr>
<td>Goodness-of-fit (AIC)</td>
<td>28,928.89</td>
<td></td>
</tr>
</tbody>
</table>

Abbreviations: $b =$ unstandardized coefficients; SE = standard error; OR = odds ratio; IRR = incident risk ratio

*p < .10; *p < .05; **p < .01; ***p < .001

5.5. Theft

Lastly, the results of the regression model for theft are presented in Table 5-5. For the logit model, more than half of the place attractors had a significant relationship with theft in the logit model. Of these significant variables, all place attractors had a negative impact on predicting the excess zeros. In other words, these place attractors are expected to have positive coefficients in the count model. At the statistical threshold of less than .001, restaurants that serve liquor ($b = -1.52$), restaurants without liquor ($b = -1.38$), retail dealers ($b = -1.05$) and bus stops ($b = -1.14$). Streetlights ($b = -0.07$; $p < .01$) also had a significant effect in the logit model, although this variable was significant at a different threshold. Furthermore, banks ($b = -1.90$; $p < .05$), convenience stores ($b = -1.28$; $p < .05$), gas stations ($b = -1.55$; $p < .05$), non-profits housing ($b = -0.84$; $p < .05$) and secondhand dealers
dealers ($b = -1.60$) had a significant effect with a p-value of less than .05. Lastly, liquors stores ($b = -2.48; p < .10$) ended up having a significant impact on theft in the logit model, although it should be noted that this variable only reached marginal significance. With respect to ranking the magnitude of the relationship, liquor stores and banks had one of the largest coefficients in this model, whereas, streetlights and non-profiting housing had one of the smallest coefficients.

Table 5-5  Zero-Inflated Negative Binomial Regression (Theft)

<table>
<thead>
<tr>
<th>Place Attractor</th>
<th>Logit model</th>
<th>Count model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b$</td>
<td>SE</td>
</tr>
<tr>
<td>Banks</td>
<td>-1.90</td>
<td>0.76</td>
</tr>
<tr>
<td>Check-cashing stores</td>
<td>-0.64</td>
<td>1.48</td>
</tr>
<tr>
<td>Community centres</td>
<td>-3.52</td>
<td>3.36</td>
</tr>
<tr>
<td>Convenience stores</td>
<td>-1.28</td>
<td>0.60</td>
</tr>
<tr>
<td>Gas stations</td>
<td>-1.55</td>
<td>0.78</td>
</tr>
<tr>
<td>Liquor Stores</td>
<td>-2.48</td>
<td>1.42</td>
</tr>
<tr>
<td>Non-profit housing</td>
<td>-0.84</td>
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</tr>
<tr>
<td>Parks</td>
<td>0.74</td>
<td>1.20</td>
</tr>
<tr>
<td>Restaurants (Liquor)</td>
<td>-1.52</td>
<td>0.30</td>
</tr>
<tr>
<td>Restaurants (No liquor)</td>
<td>-1.38</td>
<td>0.40</td>
</tr>
<tr>
<td>Schools</td>
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<td>Apartments</td>
<td>0.02</td>
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<tr>
<td>Bus stops</td>
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<td>0.14</td>
</tr>
<tr>
<td>Rental units (By-law)</td>
<td>0.37</td>
<td>0.46</td>
</tr>
<tr>
<td>Residential/commercial</td>
<td>1.19</td>
<td>0.76</td>
</tr>
<tr>
<td>Retail dealer</td>
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<td>0.20</td>
</tr>
<tr>
<td>Secondhand dealers</td>
<td>-1.60</td>
<td>0.81</td>
</tr>
<tr>
<td>Streetlights</td>
<td>-0.07</td>
<td>0.03</td>
</tr>
</tbody>
</table>

(Intercept)  3.79  0.18  44.29 ***
Goodness-of-Fit (AIC)  5,438.28

Abbreviations: $b$ = beta coefficients; SE = standard error; OR = odds ratio; IRR = incident risk ratio
*p<.10; *p<.05; **p<.01; ***p<.001

Turning to the results of the count model, several place attractors emerged as having a significant effect on predicting the counts of theft. However, only four variables that were significant in the count model were also significant in the logit model: gas stations ($b = 1.07; p < .05$), liquor stores ($b = 0.90; p < .01$), retail dealers ($b = 0.05; p < .10$) and streetlights ($b = 0.09; p < .01$). The place attractors all had positive impact on predicting
the excess zeros. For instance, gas stations had the largest effect size in the positive direction. Specifically, a one-unit increase in gas stations on a street segment increases the rate of expected theft by 190 percent. Liquor stores had the next largest effect size, considering that a one-unit increase in this place attractor on a street segment increase the rate of expected theft by 145 percent. Lastly, retail dealers and streetlights had a relatively small effect size. As such, a one-unit increase retail dealers and streetlights increase the rate of expected theft by 5 and 10 percent, respectively.

In the opposite direction, these variables had a negative impact on predicting the excesses zeros: community centres ($b = -3.46; p < .01$), parks ($b = -2.31; p < .01$), schools ($b = -4.58; p < .01$), apartments ($b = -0.09; p < .05$) and residential/commercial units ($b = -0.73; p < .01$). In other words, the increased presence of these place attractors will decrease the rate of expected theft. In terms of effect size, schools have the largest coefficient, community centres have the second largest and parks have the third largest coefficient.
Chapter 6.

Discussion and Conclusion

In the final chapter, there will be a discussion on how the results were interpreted and what are some of the possible implications. First, the limitations of this study will be discussed, followed by recommendations for criminal justice policy and directions for future research. Lastly, overall conclusions will be made about this study and the implications it has for the crime and place literature.

6.1. Limitations

First, one of the main limitations of this research is that the calculated estimates are only the relative effects and not the absolute changes from the baseline probability. The relative changes are only presented because the author is unaware of any code that would produce marginal effects for zero-inflated models. Furthermore, the code that was used to implement the zero-inflated models could not compute robust standard errors. For that reason, some of the estimates might be overestimated or underestimated. Consequently, some of these interpretations must be taken with caution. Second, this study is only a cross-sectional analysis of place data, so inferences are limited in scope. To ensure that these results are robust, the analysis should include more years of data and expand this project into a longitudinal study.

Third, there may be issues of spatial dependencies or spatial autocorrelation among the residuals of each zero-inflated negative binomial model. The spatial autocorrelation was assessed using GeoDa; the analyses indicated that the residuals were spatially dependent for all the models, except in the theft model. To correct for the spatial dependences, a spatial lag variable of the crime type was entered in the regression model; this process was completed for each statistical model. This did not change the results and the residuals remained spatially dependent. In another attempt at correcting this issue, a spatial lag variable of all the place attractors were entered in each regression model. This still did not correct the issue of spatial dependencies. Therefore, some of the estimate may potentially be inaccurate because of this issue. Further analyses should
attempt to use a zero-inflated spatial count model, which controls for spatial autocorrelation.

Lastly, the study only measured the direct impact of places on crime at each individual spatial unit. The analyses did not measure the relationship between places and crime on the surrounding street segments. This could potentially explain why certain facilities (e.g. check-cashing stores, convenience stores, etc.) did not have a significant impact on crime (i.e. BNER and BNEC) or the direction of the relationship was contrary to prior expectations (i.e. parks and schools). Despite these limitations, the results provide an informative explanation of criminal activity and have useful implications for crime prevention policy.

6.2. Discussion

First and foremost, the results of this research demonstrate that place features do have an impact on the counts of different property crimes at street segments in Vancouver. Furthermore, the results show how important it is to disaggregate the data into individual crime types, especially within the context of break and enter – see table 6-1 for the relationships between all place attractors and all five types of property crime. For instance, bus stops were significant for both crime types, although the parameters were in the opposite direction. For some reason, the number of bus stops on a street segment actually decreased the counts of BNER but increased the counts of BNEC. As a possible scenario, burglars could potentially be deterred from breaking into houses located on streets with an increased number of bus stops because these place features attract more people to the area. It makes more sense to select a target that is more secluded from large groups of people in order to avoid detection from potential witnesses. However, the logic that bus stops attract more people and deter burglars from committing crime does not appear to be applicable for BNEC, since increasing the number of bus stops on a street segment actually increases the number of BNEC. It is unclear as to why this crime type would have a positive association with bus stops because these street segments are more likely to have higher levels of foot traffic, thus having higher levels of informal guardianship. Perhaps the explanation for this contradiction between BNER and BNEC is more complex or the relationship is spurious. For example, bus stops are more likely to be located on street segments that are in commercial districts, which would have more targets to victimize. Therefore, the effect of bus stops on BNEC cannot be explained by a simple
cause and effect relationship, but rather it has more to do with the location in which these places coincide with each other. This is just a possible explanation as to why bus stops have an opposite effect on these two crime types; further investigation is required.

Table 6-1 Place Attractors and Crime Types (Significant Relationships)

<table>
<thead>
<tr>
<th></th>
<th>BNER</th>
<th>BNEC</th>
<th>TOV</th>
<th>TFV</th>
<th>THEFT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>+</td>
<td>+</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car parkades</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Check-cashing stores</td>
<td>+</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community centres</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Convenience stores</td>
<td></td>
<td></td>
<td>+</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Gas stations</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Liquor stores</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-profit housing</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Parks</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Restaurants with liquor</td>
<td>-</td>
<td>+</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Restaurants without liquor</td>
<td>-</td>
<td>-</td>
<td></td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Schools</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apartments</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Bus stops</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Rental units (By-law issues)</td>
<td>+</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential/commercial</td>
<td></td>
<td></td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Retail dealers</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Secondhand dealers</td>
<td></td>
<td></td>
<td>+</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Skytrain stations</td>
<td></td>
<td></td>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Streetlights</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: First column of each crime type indicates the results of the logit model and the second column of each crime type indicates the results of the count model. (+) indicates positive and significant impact; (-) indicates positive and significant impact; empty cell means non-significant effect.

Another example that highlights the importance of disaggregating crime data can be found in the results for restaurants with and without liquor. Regarding BNER, restaurants with liquor did not influence this crime type, although restaurants without liquor had a significant and negative impact. Similar logic applied to the relationship between bus stops and BNER can also be applied to restaurants without liquor. As such, this facility decreases the counts of BNER on a street because more people are attracted to these locations and effectively deter potential burglars. For BNEC, however, the results were reversed, and the signs were in the opposite direction; restaurants with liquor were significant and positive, and restaurants without liquor were non-significant. These mixed
results between the two crime types are rather interesting because it means that there is something qualitatively different about these places. Again, perhaps restaurants with liquor are located in parts of the city that are more prone to being victimized and where guardianship is low, such as the entertainment district or commercial areas on major arterial roads. These are just some speculations, but further investigation would also be required to explain this contradiction. Both examples described above illustrate the importance of disaggregating crime data for analysis; information would have been lost or misrepresented if the data were aggregated. Lastly, the significant relationship between car parkades and BNER found in the logit model provides some evidence to support the methodological strategy of initially including all place attractors into the model. Even though car parkades do not have a theoretically connection to BNER, the logit model shows that this place feature has a significant impact predicting the excess zeros of BNER. This result provides further statistical support to demonstrate that BNER are not likely to occur on a street segment that also has car parkades.

Moving forward, some findings were unexpected and contrary to theory and previous research. For example, increasing number of streetlights on a street segment had a positive effect on both crime types, although the magnitude of the relationship was relatively small. This result was rather surprising because this variable was intended to be an indicator of guardianship; increasing the amount of lighting is expected to deter potential criminals. It is possible that streetlights do not act as a deterrent for criminal activity when considering other place characteristics at the street segment level. Interestingly, this result is consistent with what Weisburd and colleagues (2012) found in their study. Because of these similar findings, it could be that the assumptions about streetlighting and guardianship do not hold at micro-places.

Next, the negative relationship found between parks/schools and BNEC was rather surprisingly. Previous research has shown that these places increase the levels of crime (Boessen & Hipp, 2018; LaGrange, 1999); however, those studies were not within the context of BNEC or applied analyses at street segments. This negative association could indicate that these places might be able to successfully prevent BNEC from occurring on the immediate street segments. It may be that people who frequently use park facilities or travel to schools are more familiar with each other and are able to recognize outsiders who might be potential burglars; thus, these places would have a deterrent effect on BNEC because of this informal sense of community and recreational participation. However, a
simpler explanation could be that schools and parks are unlikely to share a street segment with commercial business, which would effectively decrease the counts of BNEC.

With respect to BNER, it was surprising that schools did not have an effect on this crime type considering that previous research was able to uncover the criminogenic effect of schools (LaGrange, 1999; Roncek & Faggiani, 1985; Roncek & Lobosco 1983). However, the previous studies were not specific to BNER; instead, property crime indices and property damage offenses were used as an outcome measure to represent criminal activity. Also, these previous studies did not use street segments as unit of analysis, which could also explain some of the contradictions to previous research. However, Groff and Lockwood (2014) did use street segments as a unit of analysis and found that schools had an impact on property crimes. In other studies that were more specific to BNER, one study found that only elementary schools had a positive association with BNER – but not high schools (Kautt & Roncek, 2007). On the other hand, another study found that public schools did have a positive effect on BNER (Murray & Swatt, 2013). Although, when schools were disaggregated into individual types (i.e. elementary, middle, high school), elementary schools had a negative impact on BNER, but had a positive effect on BNER in the adjacent areas. Lastly, Willits et al. (2013) also found that high schools did not affect BNE and elementary schools did have a negative impact on this crime type.

On the surface, the non-significant relationship between BNER and schools appears to be surprising. However, when examining the results more closely within the context of previous research, there is actually a clear connection to the literature. For the studies that did discover a positive association with schools and crime, the outcome variable was a property crime index. Although the results do not align with these studies, the results of the current study did align with previous research that specifically examined BNER. Therefore, schools appear to not have a criminogenic effect on BNER. Perhaps youth cannot be considered motivated offender for this specific crime type because a BNE requires more technical criminal skills than stealing a car or damaging property. It should be noted that this place attractor was an aggregate level variable that include both elementary and high schools. Perhaps the analyses might yield different results if this place attractor was disaggregated.

In terms of consistencies between both types of break and enter, the presence of apartments and retail dealers on a street segment had a positive association with both
crime types. As such, it appears that apartments and retail dealers act as suitable targets for BNER and BNEC, respectively. However, BNER also increases when there are retail shops on the same street segments and BNEC increases when there are apartments on the same street segment. To explain this, residential units that share the same street segments as retail businesses are more likely to either be apartment buildings or apartments onto of the retail shops. The latter is likely to have inadequate security measures than stand-alone apartment buildings or detached dwelling houses, which might explain why retail shops increases the risk of BNER because these residential units are easier to break into. It is also quite possible that both variables are an indicator of suitable targets for BNER and BNEC. Perhaps these targets are not mutually exclusive to either type of crime, instead the presence of apartments or retail dealers act as a crime generator by creating more opportunities for any type of burglary.

Next, the variables that were intended to measure social disorganization (i.e. non-profit housing and rental units with by-law issues) had a significant and positive effect on BNER. However, there may be potential omitted variable bias in the BNER model because there were limited measures of social disorganization theory. Measures of socioeconomic status (i.e. unemployment rate, median household income, etc.) have shown to be important predictors of BNER in the Vancouver context (Andresen & Hodgkinson, 2018). Although it is difficult to operationalize these indicators at the street segment level, omitting these variables that specifically measure socioeconomic status from the model may affect the overall results. Therefore, other research should attempt to created more specific indicators of social disorganization considering that it has shown to be important aspect for predicting property crime.

Turning to the results for the motor vehicle-related crimes, the significant variables in the TOV model were all in the theoretically expected direction, expect for bus stops and streetlights. Bus stops are intended to describe the urban landscape and measure public accessibility. Therefore, more bus stops on a street segment is supposed to attract more people which would lead an increase in the number of convergences between potential offenders and targets. In turn, places with more bus stops should have more crime; however, the results indicate that the opposite is true, and bus stops actually decrease the risk of TOV. This result is interesting because it is contrary to what Weisburd et al. (2012) found in their study, although bus stops had a negative impact on three of the five crime types. Unlike violent offenses that require person-to-person contact (i.e. assaults and
robbery), perhaps bus stops do not actually increase the number of convergences for property offenses because the targets are stationary and cannot actually converge with offenders at bus stops. This is because people are unable to park their vehicles close to bus stops because of parking restrictions. Instead, bus stops are actually an indicator of guardianship with respect to motor vehicle-related crimes. There are likely to be more people present in areas with bus stops. Because of the increased presence of people, this will actually deter potential offenders from targeting vehicles in these areas because these people act as informal guardians. This could explain why bus stops decrease the risk of both motor vehicle-related offenses. These results further emphasize the importance of disaggregating crime data when conducting analyses.

Despite some of these results that were contrary to expectation, the results for both the TOV and TFV model support the idea that certain place features act as crime generators and attractors at street segments. For example, car parkades had a positive and significant impact on both motor vehicle related offenses. Specifically, car parkades had the largest effect size in the TFV model and the second largest effect size in the TOV model. Thus, it is evident that these place features increase the risk of both crime types because of the increased presence of targets (e.g. vehicles). Therefore, criminals are attracted to these areas because of the increased presence of vehicles to steal or break into.

More specific to the TFV model, five variables had a significant impact on this crime type that were contrary to theory and prior expectations: gas stations, bus stops, residential/commercial buildings, secondhand dealers and streetlights. It is unclear as to why there is a negative relationship between these places and TFV because these places were assumed act as crime generators. Perhaps in the context of TFV and Vancouver, these places actually decrease the risk of TFV, such as such as gas stations, residential/commercial buildings and secondhand dealers. For instance, gas stations attract people throughout most periods of the day for various reasons, which could inadvertent increase the levels of informal guardianship and therefore decrease the risk of TFV to occur on a street segment. As for residential/commercial buildings and secondhand dealers, perhaps these places are located in areas of the city that have higher pedestrian traffic that acts as a preventive measure to deter thieves from breaking into vehicles. Considering that these place attractors are only significant for TFV and no other crime type, further investigation is needed to develop more clear explanation.
The results also show that Skytrain stations act as a crime generator for TFV at street segments, although these places do not have a significant impact on the other property crime types. It makes sense that BNER would not have significant relationship with Skytrain stations because there are not as many residential units around transit stations in Vancouver. However, it was expected that this place attractor would at least increase the risk of TOV, considering that a significant relationship was found between these variables in a different Canadian city (Gallison & Andresen, 2017). Perhaps the units of analysis in the current study are too small to capture the criminogenic effect of Skytrain stations. Crimes may be occurring on the street segments that surround Skytrain stations, although this study does not take this into consideration. Further analyses should also create distance thresholds to determine if these other property crimes are occurring in the surrounding areas and not just on the immediate street segments.

Turning to the theft model, the results were able to confirm some prior expectations, although some findings were contrary to theory. For instance, it was not too surprising gas stations, liquor stores and retail dealers on a street segment increase the risk of theft to occur. This is because these places are more likely to report incidents of shoplifting, especially liquor stores and gas stations. Most often, there is a convenience store attached to a gas station, which would explain why these places increase the risk of theft because of higher incidents of shoplifting. It should also be noted that standalone gas stations are not differentiated in the data, so if a gas station does have a convenience store, it is simply classified a gas station. However, this logic does not provide an explanation as to why standalone convenience stores have a non-significant impact on theft. Perhaps these types of convenience stores have higher security measures or are located in areas of the city that have lower rates of crime.

On the other hand, it was rather surprising that schools, parks and community centres had a negative impact on this crime type. There is an expectation that there will be an increased presence of youth at these places, which would in turn increase the presence of motivated offenders and would therefore increase the risk of crime. The results show that this is not the case and these places actually decrease the risk of theft with a relatively large effect size. Although these places may attract more potential offenders, these places typically do not possess any valuable goods to steal. Schools and community centres may have expensive equipment or possessions, but the occurrence of reporting stolen items would be so infrequent that the presence of these place attractors
would not have a positive impact on theft. In fact, the significant and negative relationship of these places on theft would indicate that these place attractors may actually represent levels of guardianship and effectively decrease the risk of theft. Similar to the explanation for BNEC, people who frequently visit these places are likely to have higher levels of social or collective responsibility that could effectively deter potential offenders from stealing possessions from these places. On the other hand, perhaps theft is actually be occurring on the surrounding street segments since these places are often large polygon units that are connected to multiple street segments. Similar to the logic reasonings provide for Skytrain stations, analyses should include distance thresholds to capture the full picture of criminal activity.

Lastly, there were some general patterns across multiple crime types that are worth mentioning. For example, streetlights had a significant and positive effect in all five models of property crime. Because this place feature was intended to represent guardianship, it was rather surprising that streetlights increased the risk of criminal activity. Perhaps streetlights actually measure the levels of human activity instead of guardianship levels. If this is an accurate assumption, then the presence of more streetlights on a street segment might be an indication of a higher ambient population. This is because municipalities will likely install streetlight where there is an increase of pedestrian foot traffic. Thus, places with more streetlight have a higher presence of activity, which would therefore increase the number of convergences between offenders and targets. This is a possible explanation as to why streetlights actually increase the risk of criminal activity instead of decreasing the risk.

Next, non-profit housing units consistently had a significant and positive effect across all property crime models, expect for theft. Therefore, the results suggest that this place attractor generates different opportunities for crime to occur at the street segment level. The positive effects also suggest that there is some validity in using non-profiting housing as an indicator of lower socioeconomic status. As such, it appears that lower income housing increases the risk of both types of break and enter and both motor vehicles on a crime segment. Furthermore, magnitude of the relationship was either the largest or the second larges in each respective model. In relation to non-profiting housing and as a recommendation for future studies, research might want to consider including other housing units that are indicators of lower socioeconomic status – homeless shelters and single room accommodations (SRA). These SRAs include single room occupancy
(SRO) hotels and rooming houses that are less than 320 square feet for low-income individuals. Including these place features into the model as well might enable to the results to be more robust.

Another interesting finding was the non-significant effect banks, liquor stores, gas stations, convenience stores had on most of the property. Although these place attractors were significant in the theft model, this crime type appears to have far different patterns that the other crime types. For that reasons, most of this discussion will focus on the other property crimes. Since other studies have found that these place attractors increase criminal activity (Haberman & Ratcliffe, 2015), it is rather surprising that these places do not impact crime. However, previous studies were more specific to violent offenses that require interpersonal contact (e.g. assaults and robberies). Consequently, it would appear that places such as liquor stores or banks attract offenses that are more violent in nature and do not create a criminogenic environment to commit property related offenses. This is another reason as to why it is very important to disaggregate the crime data when performing these spatial analyses.

6.3. Criminal Justice Practice and Policy Implications

As this study produced informative and valuable insights into the spatial patterns of criminal activity at micro-places, these results also have practical implications for crime prevention policy. Understanding which facilities significantly impact property crime at street segments will enable practitioners and policy makers to implement crime prevention measures at more precise locations. Place-based crime prevention measures could potentially be more effective than programs that are implemented within large geographic units. For example, altering the physical / built environment at street segments instead of a city block might have a larger impact on preventing certain types of property crime. Target hardening or increasing natural surveillance at micro-spatial places that have demonstrated to have a chronic crime problem through empirical evidence would also be more beneficial for crime prevention and deterrence. It would be interesting to measure the effects of a crime prevention program pre-treatment/post-treatment at different geographic scales. Furthermore, knowledge of these spatial patterns could assist law enforcement agencies to implement place-based policing initiatives that could be more effective for crime control. For example, directing patrols units to specific locations where there is a greater risk of criminal activity would be a more proactive approach to policing
and could effectively prevent crime before it even occurs. Ultimately, understanding these patterns are more intuitive for crime prevention because it is easier to change the characteristics of different places than it is change the behaviour of problematic people.

6.4. Directions for Future Research

As a direction for future research, studies should attempt to include more measures of social disorganization. The literature has shown that it is important to include these concepts when conducting spatial analyses, although this type of data is increasingly difficult to obtain at the street segment level. Therefore, scholars should attempt to find creative ways to operationalize concepts of social disorganization. It would also be interesting to conduct similar analyses with different types of violent offense (i.e. assault, sexual assault, robbery, etc.). This was not possible in the current study because violent crimes are not publicly accessible in order to protect privacy. Other land-use or opportunity measures could also be included into the models. For instance, being able to identify which streets are defined as major arterial roads would be benefit since previous research has found these streets increase the risk of crime (Lu, 2006; Weisburd, 2012). Because of the limitations the data, this was not possible for the current study. Furthermore, temporal structures could be included into the analyses (i.e. day of week, time of day, seasonality measures). For example, BNER and BNEC are most likely to occur at different times of the day because of the guardianship factor (e.g. BNER likely to occur during the day – people are at work, and BNEC likely to occur during the night - business are closed and people are home). Analyzing the temporal and spatial components of crime together will further contribute to the knowledge and understanding of criminal activity at micro-places. Finally, different analytical techniques or statistical model should be considered for future studies. As mentioned previously, the current study only measured the impact of different places at the immediate street segments. Further research could incorporate a spatial effects model and measure the criminogenic influence that places have on nearby street segments. In terms of other statistical methods, future studies should consider applying risk terrain models to discover which factors have a significant impact on increase the risk of property crime at street segments in different Canadian cites. Lastly, other studies could apply a conjunctive analysis of case configuration to uncover the unique behaviour settings of different street segments. For instance, street segments with a specific combination of place features might have a
higher risk of crime than other place combinations. Considering these interactions between different facilities would definitely strengthen the findings of this study.

6.5. Conclusions

Overall, the results show that place features and certain facilities do have a significant effect on property crime at the street segment level. However, depending on the type of property crime, only a select number of facilities had a significant impact on crime and the relationships varied in magnitude and direction. In addition, this study attempted to operationalize key concepts from predominant theories in spatial criminology and was able to show that these concepts are important for explaining crime patterns at the street segments. Because very comprehensive datasets are needed to measure socioeconomic factors at micro-places, the statistical models of the current did not include many factors of social disorganization because of limited access to data. Therefore, future studies should attempt to develop innovative methods to measure socioeconomic and sociodemographic characteristics at street segments. Furthermore, understanding what causes crime to concentrate at such a small number of places has very practical implications for crime prevention initiatives and crime control strategies. As such, knowing which facilities increase the risk of criminal activity will enable law enforcement personnel to target hotspots of crime and direct limited resources to specific locations. To conclude, this research has contributed to the crime and place literature by uncovering some of the explanatory factors of crime at micro-spatial units and has shown that street segments are important for uncovering the patterns of crime within Vancouver.
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