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**EXPLAINING THE CO-MOVEMENT OF CRIME BETWEEN URBAN
NEIGHBOURHOODS: A STUDY OF CLEVELAND AND CHICAGO**

By

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A thesis submitted in partial fulfilment of the requirements for the degree of
Doctor of Philosophy

The University of Sheffield
Faculty of Social Science
Sheffield Methods Institute

Submission Date

20 June 2022

Acknowledgement

First and foremost, I would like to thank my *Lord, Allah*, whose favour on me is always great, for giving me the power and the knowledge to pursue my postgraduate studies abroad. Without His support and mercy, I would not have been able to make it through this long journey.

I would like to express my sincere appreciation to my supervisors **Prof. Gwilym Pryce** and **Prof. Nathan Hughes** for their invaluable advice, continuous support, and patience during my PhD journey. Your mentorship and encouragement were paramount in helping me broaden and sharpen my skills and obtain research experience. Also, a very special gratitude goes to **Prof. Patrick Sharkey** for coming on board as an additional informal supervisor. In addition to his immense knowledge and plentiful experience, he enabled me to access extensive data that would not otherwise have been available to me.

I would also like to thank **Prof. George Galster**, **Prof. Jon Bannister**, **Prof. Todd Hartman**, and **Dr. Andrew Bell** for their insightful and constructive comments and suggestions in the earlier stages of the work.

To my parents **Kamel** and **Motirah**, my brothers **Moath**, **Khalid**, **Salah**, **Abulmohsen**, and my sisters **Kholud**, **Abeer**, **Mariam**, and **Bayan** and, I am really in shortage of words to express how I'm lucky to have you in my life. I am truly at a loss for words to express how lucky I am to have each of you in my life. I never did and never will forget when I left you for my doctoral studies in the UK. Nor will I forget the central question that each of you asked me: "when will I finish my studies and return home?" My

answer was “soon,” but little did I realize that “soon” would last for eight increasingly long years! Now, at last, I can say that “soon” has become “very soon.”

My wife **Samiah**, and my children **Tamim** and **Thikra**, completing my post graduate studies abroad in general and this thesis in particular would not have been possible without your love, support and patience. You have always been the remedy for the tough days.

My sponsor Ministry of Education, Northern Border University, and Saudi Cultural Bureau, my PhD would not have been possible without you, thank you all.

Abstract

Extensive research has been carried out on neighbourhood crime over the past few decades. Prior research has emphasized the spatial clustering, similarity and stability of crime rates in different spatial units such as street segments and neighbourhoods. However, there is still very little understanding of neighbourhoods' interdependencies beyond the role of geographical proximity. The primary aim of this 'three-paper' thesis was to gain an understanding of the underlying factors that are associated with the crime co-movement of neighbourhoods, especially the effects of spatial proximity, social proximity, social frontiers, people movement flows, and other diverse factors on inter-neighbourhood connections relative to crime dynamics. This project was the first, to my knowledge, that used social network analysis to investigate why some neighbourhood crime rates move in tandem. Using network theory as the conceptual framework for the co-movement of crime across neighbourhoods, I have been able to (i) create reasonably comprehensive portraits of neighbourhood crime dynamics networks and (ii) provides insights into the attributes and possible underlying mechanisms linking neighbourhoods to one another. A number of implications have emerged from this research for policy, theory, methodology, and future research.

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CHAPTER 1

Introduction

1.1 Introduction

Extensive research has been carried out on neighbourhood crime over the past 80 years. Prior research has emphasized the spatial clustering and stability of crime trajectories over time in spatial units such as street segments and neighbourhoods. Despite these research efforts, the mechanisms driving neighbourhoods' crime co-movement have not been explored with statistical methods that can accommodate the full range of potential dependencies between observational units. This is likely because the literature has largely relied on traditional analysis methods that assume that observational units are independent, or permit dependence in very specific ways, such as spatial contiguity or proximity. Furthermore, whilst a growing body of literature has recognised the importance of moving beyond a focus on the intra-neighbourhood setting to recognize the importance of connections between neighbourhoods, there has been little research on the structure of neighbourhoods interdependencies.

The aim of this thesis was to gain an understanding of neighbourhoods' interdependencies and explore the potential underlying factors that drive the co-movement of neighbourhoods' crime trajectories. Exploring the neighbourhoods interdependencies is more likely to improve our understanding of neighbourhood crime dynamics and lead to more effective crime prevention policies. In particular, this thesis aims to explore the effects of spatial proximity, social proximity (homophily), people's movement flows, and other diverse factors on inter-neighbourhood connections relative to crime dynamics. I focus on two primary research questions: Why, in a given city, are changes in the crime rates of one neighbourhood linked to changes in the crime rates of other neighbourhoods yet disconnected from changes in other neighbourhoods? And, what factors

make two neighbourhoods' crime rates move in tandem? The first question focuses on the potential mechanisms that causes neighbourhood trajectories to move in tandem. In particular, whether neighbourhoods move together because they are part of the same community (i.e., distance is a proxy for similar dynamics), they have similar population characteristics (i.e., homophily), and/or thirdly, they are linking people together through direct interactions. The second question focuses on determining the most relevant neighbourhood characteristics in suggesting homophily between pairs of neighbourhoods which is expected to contribute to the co-movement of crime. The thesis started with clustering analysis and then two types of regression models in the second chapter in order to answer these questions using annual rates of property crime and selected neighbourhoods' characteristics. Whilst clustering neighbourhoods on the basis of similarity of crime trajectories, these clusters remain a 'black box' in the sense that much of the underlying structures of interdependence remain hidden because we cannot observe the pairwise connections between neighbourhoods or analyse the characteristics that drive them – we can only observe and explain group-level connections between clusters of neighbourhoods. Therefore, using social network analysis and exponential random graph models, more comprehensive conceptual frameworks were developed in Chapter 3 and Chapter 4. Using network theory as a conceptual framework for thinking about the co-movement of crime across neighbourhoods has enabled the analysis to be framed in a way that makes the research questions amenable to statistical network methods. Thus, such analysis helped to examine both the potential mechanisms to answer the first question and the most relevant neighbourhood characteristics in suggesting homophily between pairs of neighbourhoods to answer the second question.

To set the scene for this research, I briefly summarise below the emergence of research on neighbourhood crime dynamics in a discipline historically preoccupied with a focus on the

individual. I use this discussion to motivate the approach used in the thesis, highlighting the key gaps in the literature that I aim to address. The format of the thesis follows the ‘three paper model’, with the three papers presented in chapters 3, 4, and 5 respectively. These are summarized in sections 1.9, 1.10, and 1.11, followed by the key conceptual mechanisms in section 1.12 and a short conclusion summarizing the main findings in section 1.13.

1.2 Emergence of Research on Neighbourhood Crime Dynamics

Offender-centred research (e.g., Eck and Eck, 2012; Nettler, 1978, Sherman, 1995) has been the main focus of criminologists for many decades (Weisburd et al., 2012), commonly exploring why some individuals, and not others, get involved in criminal activity (e.g., Akers, 1973, Gottfredson and Hirschi, 1990, Raine, 1993), and the impact of particular forms of punishment and intervention in reducing re-offending (e.g., Andrews et al., 1990; MacKenzie, 2006; Mitchell, Wilson, and MacKenzie, 2007). The common denominator in this research is the assumption that individuals are the key components in the crime problem (Weisburd et al., 2012).

Acting on this assumption, scholars, policy makers, and practitioners have naturally concluded that crime prevention is possible only if they focus primarily on criminals (Weisburd et al., 2012). However, dissenting voices began to reconsider this “offender-focused” model of crime and justice, which dominated the field of criminology during the last century (e.g., Kramer, 1984; Sutherland, 1947). According to many critics of the model, offender-centred research should strengthen society’s ability to identify who will be future first-time offenders, when they will commit a crime, and what type of crime they are likely to commit. However, previous criminological research has encountered serious difficulties in making these predictions (e.g., Albrecht and Moitra, 1988, Auerhahn, 1999, Barnett and Lofaso, 1985, Bersani et al., 2009, Sampson and Laub, 2003). The voices calling for a new approach to these topics include those of

Brantingham and Brantingham (1990, P. 19): “If traditional approaches worked well, of course, there would be little pressure to find new forms of crime prevention.”

Traditionally, criminologists and crime-prevention strategies have considered the crime problem from two quite distinct perspectives: the people-centred perspective and the context perspective (Miethe and Meier, 1994). The people-centred perspective focuses on why and when an individual commits a crime and when an individual becomes a victim. According to the rational choice theory, criminals decide whether or not they will commit a crime by evaluating the costs and benefits associated with the crime: if the benefits seem to outweigh the costs, the criminals will likely pursue the crime (Clarke and Cornish, 1985, Felson and Boba, 2010). Routine activity theory posits that individuals are more likely to be suitable victims when they lack a capable guardian and when they cross paths with motivated offenders (Cohen and Felson, 1979). In contrast to the people-centred perspective, the context perspective prioritizes the important role played by place characteristics (Miethe and Meier, 1994). In their groundbreaking work, Brantingham and Brantingham (1984) formulated a comprehensive perspective of crime known as crime pattern theory: it explores the interactions of offenders, victims, and opportunities across time and space. The crime-pattern theory also explains the key role that places and their characteristics play in influencing the likelihood of a crime and how places become crime hot spots. This is broadly part of situational crime theory, which emerged out of Sutherland’s work in the 1940s that argued that crime was either "historical" impacted by past personal history or "situational" the ambient factors surrounding the crime scene and calling for criminologists to pay more attention to the concept of "situation".

While traditional criminology has focused on the individual perspective and the criminal nature of offenders, situational crime prevention is a multi-stage procedure that aims to understand

the important role played by place characteristics and how crime incidents occur. Thus, the criminology of place puts geography in the spotlight and aims to improve understanding of the place characteristics associated with crime. Prior criminology of place research showed that a place-centered approach has several advantages. First, in the place-centered approach, the focus is on where the crime occurs instead of who commits the crime and why. This approach contributed to the formulation of several theories that have improved the understanding of the factors conditioning crime in place, which in turn helped to develop more effective crime prevention strategies. For example, social disorganization theory, developed by Shaw and McKay (1942), found that informal social control has previously proved an effective inhibitor of neighbourhood crime. By focusing on crime and place characteristics, Sampson et al. (1997) extended the social disorganization theory to formulate a collective efficacy theory. The collective efficacy is defined as the ability of neighbourhood and community residents to recognize their common values and maintain social control, thus promoting collective efficacy and enabling them to act as capable guardians. Such mechanisms have been documented in studies of crime and appear strongly correlated with: (1) community social cohesion (Bellair and Browning, 2010); (2) residential stability (Sampson and Groves, 1989; Hipp, 2007); and (3) rates of home ownership (Dietz and Haurin, 2003). By contrast, weak collective efficacy was found in neighbourhoods possessing: (1) high levels of heterogeneity; (2) low economic status; (3) family disruption; and (4) high residential mobility (Sampson and Groves, 1989; Harcourt and Ludwig, 2006). Second, a significant amount of crime is committed by unknown offenders. Therefore, focusing on places rather than offenders has led to several crime prevention approaches, such as situational crime prevention (SCP). Situational crime prevention (SCP) is an approach that "seeks to reduce opportunities for specific categories of crime by increasing the associated risks and difficulties and

reducing the rewards" (Clarke, 1995, p. 91). Since the development of the crime prevention approach, researchers have published a list of techniques aimed at reducing a variety of crime types such as increasing the effort of crime, increasing the risks of crime, reducing the rewards of crime, reducing provocations, and removing excuses (e.g., Clarke & Homel, 1997; Clarke, 2003; Wortley, 2001).

Hence, owing to the limitations identified in criminal-centred criminology, the "criminology of place" (Sherman et al., 1989) has emerged as a perspective of considerable interest among criminologists (Weisburd et al., 2012). There have been a number of studies exploring crime rates across various geographic units, including states (Loftin and Hill, 1974), cities (Baumer et al., 1998), neighbourhoods (Byrne and Sampson, 1986, Schuerman and Kobrin, 1986, Bannister et al., 2018), and micro-units such as street segments (e.g., Weisburd et al., 1992, Groff and La Vigne, 2001, Weisburd et al., 2012). Although such "macro" geographic units as cities and counties have been the primary focus of many previous place-of-crime studies, a spate of more recent studies have tackled such "micro" units of place as neighbourhoods (e.g., Bannister et al., 2018; Raleigh and Galster, 2015) and street segments (e.g., Weisburd et al., 2012). In recognizing the importance of understanding area-related crime, in their seminal work on routine activity theory, Cohen and Felson (1979) suggested that "a crime is expected to occur when suitable victims, motivated offenders and the absence of capable guardians converge in space and time". Cohen and Felson provided an intriguingly original perspective on crime when they proposed that crime-prevention strategies could better address the problem of crime by focusing not only on criminals but also on crime sites.

Recent developments in crime research have highlighted the potential practical benefits of studying crime from a geographic perspective. The past few decades have seen increasingly rapid

advances in this field such as the emergence of the crime ‘hot spots’ and hot spot policing that involves centring police endeavours in the small areas that have a high crime intensity. A considerable amount of the literature revealing that a few concentrations of criminal activity across neighbourhoods and smaller geographic units can have a massive effect on citywide crime rates (Brantingham and Brantingham, 1999, Sherman et al., 1989, Weisburd et al., 1992). For instance, Sherman et al. (1989) undertook one of the seminal studies in crime concentration and clustering in Minneapolis, Minnesota, and found that only 3 percent of addresses produced 50 percent of all calls to the police. Similarly, Weisburd et al. (2004) found that, over a fourteen-year period, 4 to 5 percent of street segments accounted for 50 percent of the annual crime incidents in Seattle, Washington. Studies on place-focused crime can reveal far more than that crime is clustered in a small number of places. For example, several studies revealed that sites of crimes exhibited a high degree of stability over time—that is, they continued to be hot spots for criminal activity (e.g., Spelman, 1995, Taylor, 2018, Weisburd et al., 2004). Hence, previous studies covering crime concentration and stability have highlighted the potential practical benefits of place-centred crime analysis for crime prevention strategies. One practical benefit of such analyses is their efficient focus on a small number of “hot spots” which can significantly exacerbate the crime problem but which can be effectively handled without inefficiently spreading police resources over expansive urban areas (Weisburd et al., 2012).

Conducting a series of field trials, Braga (2001, 2005, 2007) showed with empirical rigour that hot-spot policing can result in noteworthy reductions in crime and disorder. In addition, a committee at the National Research Council, which seeks to improve public policy, reviewed police policies and practices and concluded that

there has been increasing interest over the past two decades in police practices that target very specific types of crimes, criminals, and crime places. In particular, policing crime hot spots has become a common police strategy for reducing crime and disorder problems. While there is only preliminary evidence suggesting the effectiveness of targeting specific types of offenders, a strong body of evidence suggests that taking a focused geographic approach to crime problems can increase the effectiveness of policing (Weisburd and Eck, 2004, P. 35).

In recent years, a growing body of crime-and-place literature has shifted its focus from hot-spot criminology to the patterns of crime trajectories over time. The purpose of crime trajectory analysis is to understand the development of crime over time by studying the long-term patterns of crime within a geographic unit. Weisburd et al. (2004) was an early work that employed a trajectory analysis of crime and place. Using data pertaining to street crimes that had been committed between 1989 and 2002 in Seattle, Washington, the researchers were able to identify eighteen unique trajectories that characterized crimes committed at the street-segment level. Several studies followed Weisburd et al. (2004) and similarly examined crime trajectories at micro-geographic units such as street segments and intersections (e.g., Curman et al., 2015, Weisburd et al., 2009, Groff et al., 2010). These studies revealed a considerable concentration and stability of crime over time. It has been noted that a society's understanding of crime patterns has a great bearing on the allocation of crime-prevention resources (Sherman, 1995, Weisburd et al., 2004) and has the potential to heighten the efficacy of police intervention.

1.2.1 What is Neighbourhood?

Urban sociology was founded by Robert Park and Ernest Burgess, who described local communities as "natural places" that grew out of the rivalry between enterprises for land use and

population groups for affordable housing. A neighborhood, according to the perspective of the local communities, is a subsection of a broader community—a group of both institutions and individuals living in a geographically defined region that is influenced by ecological, cultural, and occasionally political forces (Park 1916, p. 147–154). Galster (2001, p. 2112) defines neighbourhood as "the bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses."

In practice, most social scientists and the prior neighbourhood crime research rely on geographic boundaries defined by the Census Bureau and other administrative agencies (e.g., police districts). Even though officially defined units like census tracts and block groups are reasonably congruent with the idea of overlapping and nested ecological structures, inadequate operational definitions of neighbourhoods exist for study and policy (Sampson et al., 2002). Selecting a geographic analytic unit is a common challenge in ecological investigations (Hipp, 2007). In the spatial criminology, the influence of various analytical geographic units has received a lot of empirical attention. "Small is better" is an approach that many recent crime and place academics have adopted since micro-level units reduce within group heterogeneity (Oberwittler and Wikstrom, 2009). In this regard, several academics have suggested that using larger analytical units to describe neighbourhoods and communities, such as U.S. census tracts and block groups, obscures significant street-to-street variability in crime within neighbourhoods (Weisburd et al. 2012; Andresen and Malleson 2011). In summary, these researchers contend that empirical studies that concentrate on neighbourhoods and communities miss a large portion of the spatial heterogeneity in urban crime issues (Eck and Eck 2012; Weisburd 2015). Other scholars, however, argue that micro analytical geographic units may not be appropriate in all contexts because some social processes and human behaviours take place at a larger spatial scale (Boessen and Hipp 2015;

Hunter 1985). The tendency of recent research to focus on too narrow of a geographic lens is concerning as researchers may miss significant processes that occur at a wider spatial scale (Boessen & Hipp 2015). Studies of micro geographic units such as street blocks rarely consider the surrounding social context or more meso scale communities at the same time. For example, the ethnic heterogeneity of a micro geographic units could provide too narrow of a lens and might miss broader patterns in the surrounding area.

The neighbourhood level was chosen in this thesis for two reasons. First, the data availability of both crime rates and neighbourhood characteristics. US census data is not released at the level of micro places, such as street segments. Thus, given this research aims not only to study the crime trajectory but also examine the impact of area characteristics, the use of smaller geographic units with the lack of data would be inappropriate for this research. Thus, using neighbourhood level allows me to determine the co-movement of crime trajectories, and examine the potential mechanisms that drive such patterns using neighbourhoods' characteristics. Second, since the ground-breaking work of the Chicago School in the early 20th century, a significant body of literature has investigated the ecology of crime. These studies and formulated theories have often used neighbourhood as a geographic unit. Thus, neighbourhood was selected to build on the decades of research conducted at these geographic units.

This thesis will use Census Tract CT, which is an area roughly equal to a neighbourhood, with a population ranged between 1200 and 8000. CTs were established by the US Census Bureau for the purposes of analysis and used in the literature to represent neighbourhoods. Neighbourhood is different from other micro geographic units such as street segments, blocks, and block groups that have been used in prior crime and place research. Street segments are the parts of a street between two intersections. A bigger unit is the block, which is defined by the US census as an area

that is "bounded by visible features, such as streets, roads, streams, and railroad tracks, and by nonvisible boundaries, such as selected property lines and city, township, school district, and county limits, and short line-of-sight extensions of streets and roads." Generally, blocks are small in area; for example, a city block is bounded on all sides by streets. Block groups are statistical divisions of census tracts that consist of clusters of blocks. Within the standard census geographic hierarchy, block groups never cross state, county, or census tract boundaries but may cross the boundaries of any other geographic entity.

1.3 From intra-neighbourhood to inter-neighbourhood

Scholars have recently moved beyond a focus on the intra-neighbourhood settings to recognize the importance of inter-connected neighbourhoods (also termed 'neighbourhood networks'). Research addressing this topic has argued that our common notions of social networks and personal relations should not prevent us from extending this same conceptualization to the ties that link neighbourhoods together: "neighbourhoods are themselves nodes in a larger network of spatial relations" (Sampson, 2004). In the words of (Mears and Bhati, 2006), "communities do not exist in isolation.... They may affect and be affected by other communities with which they coexist and interact". Thus, recent studies have argued that social proximity, as well as spatial proximity, promote criminogenic ties among neighbourhoods. Social ties, which are "spatially unbounded," connect individuals with others from distant areas through several channels (Wellman, 1999a, Mears and Bhati, 2006), such as focal institutions and homophily (i.e., the general propensity to associate with like people) (Papachristos and Bastomski, 2018b).

From this view, people are most likely to develop relationships with others who live closest to them. Thus, neighbourhoods are conceptualized as interdependent "nodes in a larger network of spatial relations," rather than independent units of analysis, and the main ties in this network

are defined geographically (Sampson, 2004). Previous research on neighbourhood networks, although it has investigated neighbourhood ties and the factors that foster them, has focused largely on the topics of co-offending (Papachristos and Bastomski, 2018a, Schaefer, 2012) and gang networks (Papachristos et al., 2013).

1.4 Limitations with the Crime-and-Place and inter-neighbourhood Literature

Thus far, the crime-and-place literature has identified two important themes. First, place-centred criminology research has confirmed that crime occurs in significant, stable geographical concentrations over time. Second, certain place features appear to be associated with higher crime rates. However, previous empirical research in the field of place-centred criminology has suffered from a number of limitations. First, research on crime trajectory analysis has been restricted mostly to the micro-geographic level, with little attention being paid to crime that occurs in larger geographic units such as neighbourhoods (Groff et al., 2010, Raleigh and Galster, 2015). Sampson et al. (2002) stated that “there is a clear need for rigorous longitudinal studies of neighbourhood temporal dynamics.... We have scant information on how neighbourhood processes evolve over time” (p. 472). Bannister et al. (2018) noted that “research engaging with narrower geographies might fail to capture the ‘bigger picture’” (p. 178).

A second limitation in place-centred criminology is its general disregard for factors that may explain similarities and differences between neighbourhoods. Prior research has produced mounting evidence of similarities in crime trajectories at geographic units. However, the research has typically dedicated itself to confirming both concentrations of crime and stability in crime trajectories in individual geographic units; that is, the research has by and large overlooked factors that perhaps cause either variability or, for that matter, an absence of variability between neighbourhoods. A systematic understanding of why certain groups of neighbourhoods have

experienced similar crime trajectories is still lacking in the literature. Therefore, greater availability of data collected from various geographic units would motivate researchers to investigate how rates of neighbourhood crime evolve over time and how the characteristics of neighbourhoods and the trajectories of criminal activity are associated with each other.

A third limitation is that previous neighbourhood network studies, while examining co-offending networks, have overlooked inter-neighbourhood connections in crime dynamics and the extent to which factors other than spatial proximity determine the co-movement of crime. Hence, the main focus of prior research into neighbourhood networks has largely focused on co-offending and gang networks rather than neighbourhood-level crime trajectories.

Fourth, existing research relies on various forms of regression analysis to investigate inter-neighbourhood crime dynamics. This methodological approach to the data is problematic because it rests on the assumption that observations are either conditionally or unconditionally independent of one another (Contractor, Wasserman and Faust, 2006; Harris, 2014). This assumption makes regression analysis less than ideal, to say the least, if the very purpose of the analysis is to estimate the degree of dependence between neighbourhoods (Dean and Pryce, 2017). Spatial econometric methods such as exploratory spatial data analysis and spatial regression models (Anselin et al. 2000) relax this assumption but in a very specific and limited way; for example, the methods allow for dependence between neighbourhoods that are contiguous or in close proximity. Distant neighbourhoods are assumed to be unconnected to one another. The standard spatial regressions are methodologically useful and used widely to study the crime diffusion and clusters (e.g., Meares and Bhati, 2006; Tita and Radil, 2010a, 2011). However, such models are imprecise to study the interdependency between neighbourhoods as “they model the diffusion of crime as if it spreads like an airborne pathogen” (Papachristos and Bastomski, 2018a). Furthermore, the standard spatial

regressions are useful in simply demonstrating and mapping the crime patterns more than explaining the causes of the crime clusters (Radil et al., 2010). Thus, relying on such models is considerably imprecise to explain the complicated intercommunity social processes driving crime patterns (Leenders, 2002). Therefore, if we want to understand how, in crime dynamics, inter-neighbourhood linkages might emanate from a range of factors that go beyond the distance and contiguity factors, then we need to employ methods designed specifically for the analysis of networks. However, as far as I am aware, network methods have yet to be applied in the literature on crime dynamics.

1.5 Aim

The aim of this thesis is to gain an understanding of neighbourhoods' interdependencies and explore the potential underlying factors that are associated with the co-movement of neighbourhoods' crime trajectories. This general aim gives rise to three key objectives and two primary research questions, as follows.

1.6 Objectives

- Objective 1: Use network theory to understand the co-movement of crime across neighbourhoods.
- Objective 2: Provide a conceptual framework for thinking about the structure of inter-neighbourhood connections and crime.
- Objective 3: Explore the mechanisms generating similarity in temporal dynamics of neighbourhood crime.

1.7 Primary research questions

- RQ 1: Why, in a given city, are changes in the crime rates of one neighbourhood linked to changes in the crime rates of other neighbourhoods yet disconnected from changes in other neighbourhoods?
- RQ 2: What factors that make two neighbourhoods' crime rates move in tandem?

These two primary questions inform the three-paper approach, with each paper addressing one or both through a focus on more specific research questions.

1.8 Contribution

This three-paper thesis contributes to the criminology of place literature by addressing the aforementioned limitations of prior work and making several contributions to the existing literature. First, to my knowledge, no previous research has used social-network analysis to investigate why some neighbourhood crime rates move together. This omission in the literature is important not only for methodological reasons but also because network analysis offers a powerful conceptual framework for thinking about the co-movement of crime. Second, conceptualizing the co-movement of crime as a type of network has three key advantages: (1) it provides a more coherent and comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in crime; (2) it provides a more appropriate empirical framework for analysis that is not constrained by the prohibitive assumptions of node independence assumed in traditional regression analysis; and (3) provides insights into the mechanisms linking similar neighbourhoods to one another. Third, in this thesis, I examined the added value that arises when one considers homophily, mobility flows, social frontiers, and the historical discrimination of redlining maps. In these regards, my overall research findings constitute evidence that the

aforementioned factors may serve as underlying mechanisms that drive the co-movement of crime across neighbourhoods.

1.9 Chapter 3 Overview

A considerable amount of literature has examined the crime trajectories of such micro places as street segments and intersections (e.g., Weisburd et al., 1992, Groff and La Vigne, 2001, Weisburd et al., 2012). Although this branch of the literature has revealed that crime in these places is highly concentrated and highly stable over time, a closer examination of the literature on crime-trajectory analysis reveals that relatively little attention has been paid to crime trajectories in larger places, including neighbourhoods. Furthermore, previous studies have focused almost exclusively on crime-rate trajectories as they relate to geographic units over time. What remains unclear, however, is why some neighbourhoods appear to have similar crime trends. To address this issue empirically, one might reasonably suspect that various neighbourhood characteristics, systematically shape similar crime-trajectory clusters in distinct neighbourhoods.

To address these issues in this chapter, I set out to answer three questions: (1) Do neighbourhoods, in a given city, experience disparate crime trajectories? (2) Are there systematic drivers of trajectory group membership? (3) Are there structural differences in the determinants of crime levels across distinct neighbourhood crime trajectory groups?

In this chapter, I analyse property-crime data of Cleveland, Ohio, for the period between 2010 and 2017. This chapter rests on a three-step approach to analysing crime trajectories at the neighbourhood level. For Step 1, I cluster neighbourhoods by their crime trajectories. Specifically, I use the k-means clustering method to identify groups of neighbourhoods experiencing similar crime trajectories over time. In making this identification, I rely on the annual property crime rate of neighbourhoods from 2010 to 2017. For Step 2, I use multinomial logistic regression to test

whether or not there were systematic drivers of trajectory group membership. Finally, for step 3, I used multiple regression to test for structural differences among distinct crime-trajectory groups of neighbourhoods regarding possible determinants of crime.

Having performed Steps 1 through 3, I was able to identify three groups of neighbourhoods on the basis of the annual crime rates over the study period: Group 1 consisted of neighbourhoods with an increasing crime trajectory (increase by 48%); Group 2, those with a decreasing crime trajectory (decrease by 22%); and Group 3, those with a stable crime trajectory (no major change). Then, using multinomial logistic regression, I established whether or not there were systematic drivers of this group membership. A broad range of neighbourhood characteristics (i.e., poverty, unemployment, family disruption, ethnic heterogeneity, residential instability, age composition, and business premises) were brought together into a single model that examined their influence on group membership. The resulting analysis revealed notable differences in terms of the influence of some variables on group membership. For example, some variables were found to reduce the probability of a neighbourhood being in one group, but the likelihood of being in the other group reduced by different variables. Similarly, some variables were found to increase the likelihood of being in a one group, but do not have an impact on the other group membership. These findings show that the membership of different neighbourhood groups is influenced by different factors. Finally, using multiple regression, I examined whether or not there were structural differences among the three neighbourhood groups with respect to the determinants of crime levels. The results revealed that some of these neighbourhood characteristics varied significantly across the three neighbourhood groups. The neighbourhood characteristics (poverty, family disruption and business addresses) significantly and positively associated with crime rate. However, significant differences of their effect seen in the interaction model results. Thus, the interaction test results

confirmed that same variable may operate differently in different groups. For example, a significant difference in all significant variables effects was found between group 1 and group 2. Also, a significant difference was found in the poverty rate effect between group 1 and group 3. In other words, the results show that poverty, family disruption and business addresses affect crime rate but they affect crime rate in group 1 by substantially more than affect crime rates in group 2 and 3. In summary, some of the neighbourhood characteristics effects were present to varying degrees in the three groups.

1.10 Chapter 4 Overview

A growing body of literature has moved beyond a focus on intra-neighbourhood settings to recognize the importance of understanding the connections between neighbourhoods. These inquiries, however, often focus on co-offending networks and overlook both the inter-neighbourhood connections in crime dynamics and the extent to which factors other than spatial proximity determine the co-movement of crime. New research on the underlying connections between neighbourhoods can bolster our understanding of the potential drivers of crime dynamics.

In the third chapter, I focus on two research questions: (1) To what extent does homophily and spatial proximity explain the co-movement of property crime across Cleveland's neighbourhoods? and (2) To what extent does social frontier and the historical discrimination of redlining maps explain the co-movement of property crime across Cleveland's neighbourhoods?

If crime dynamics are said to be homophilous, it means that neighbourhood A and B are more likely to be connected in terms of co-movement of crime if they have similar attributes. My aim for this chapter is to explore the underlying factors that are associated with the co-movement of crime trajectories across neighbourhoods.

For Chapter 3, I use a network-analysis method to explore the extent to which mechanisms such as neighbourhoods' spatial proximity and socioeconomic and demographic similarity can predict the co-movement of crime. To this end, I develop a network of crime dynamics where ties between neighbourhoods take shape if the neighbourhoods' crime rates move in tandem. Using US census data and crime-trajectory data from the American city of Cleveland, in the Midwestern state of Ohio, I define a neighbourhood network concerning the co-movement of crime. The network that I define on the basis of the aforementioned data therefore consists of nodes (i.e., neighbourhoods) and the edges that link them. A link is said to occur between two nodes if there is a high correlation over time in their crime-rate dynamics.

I adopt a two-stage analytical strategy. The first stage consists of a descriptive analysis targeting the distribution of crime co-movement ties across neighbourhoods. The aim of this analysis is to determine the degree to which spatial proximity among neighbourhoods explains crime co-movement ties. Second, I estimate a set of exponential random graph models (ERGMs) in order to investigate the characteristics of neighbourhoods that foster crime co-movement therein focusing on the impact of spatial proximity and social proximity.

I use the 2010 US Census data to obtain several neighbourhood characteristics. The measures are neighbourhood disadvantage, non-white percentage of the population, residential instability, family disruption, and historical redlining maps.

The results of the two-stage analysis in chapter 3 reveal three key insights. First, the results of the spatial-proximity portion of the analysis are robust in all models, indicating that spatial proximity was significantly associated with the co-movement of property crimes between neighbourhoods. Second, interestingly, the higher a neighbourhood's level of disadvantage was, the more likely the neighbourhood would be to experience crime trajectories similar to those

characteristic of relatively affluent neighbourhoods. In other words, similarity in disadvantage level reduced the likelihood of crime co-movement ties between neighbourhoods. However, in examining what brings dissimilar neighbourhoods together, I found that contiguity appears to have been a potential driver and showing a social frontier effect. Lastly, the model with the best fit includes all measures together, indicating that both spatial proximity and social proximity are key determinants of crime co-movement networks.

1.11 Chapter 5 Overview

A great amount of criminology research has addressed both the concentration and the distribution of violence, especially in urban settings. In this regard, previous empirical studies have emphasized the spatial clustering of violent crime, the non-randomly distributed of violence across neighbourhoods, and the spills over of violent crime into nearby neighbourhoods. Previous empirical studies examined the neighbourhood characteristics that were thought to entail higher violence rates in multiple neighbourhoods in a given city. However, beyond the factor of geographical proximity, little has been revealed about the specific mechanisms responsible for the dynamic of violence across neighborhoods.

In this chapter, I draw on previous research examining the relationship between neighbourhood networks and crime in order to answer two research questions: (1) What is the impact of people's movement flows on the co-movement of shooting incidents across Chicago's neighbourhoods? (2) To what extent does homophily and spatial proximity explain the co-movement of shooting incidents across Chicago's neighbourhoods?

In this chapter I analyse the co-movement of shooting incidents over the six-year period between 2014 and 2020 in the major US city of Chicago. Using shooting-incident data, a mobile phone origin–destination (MPOD) dataset, and US census data, I estimate a set of exponential

random graph models (ERGMs) to investigate the attributes of neighbourhoods that foster the co-movement shooting incidents.

The findings of this study show the homophily effect of socioeconomics between neighbourhoods in ways that increase the probability of shooting ties. In particular, similarity in poverty levels and in the black and youth segments of a population seem to significantly increase the likelihood that shooting-incident co-movement ties will form between neighbourhoods. I also assess evidence that people's movement flows across neighbourhoods significantly influence the co-movement of shooting incidents. That is, the larger a movement flow is between neighbourhoods, the more likely it will be that shooting-incident co-movement ties will take shape across the neighbourhoods.

Also, the findings suggest a role for spatial proximity in explaining why neighbourhoods shooting incidents move together; and part of the explanation is driven by flows of movement. This becomes clearer when ties to adjacent tracts removed; that shows that proximity still matters, but much less so - and flows of movement are still a core part of why proximity matters. Hence, neighbourhoods move together in part because they have similar composition, and in part because of the movement flows of people tie neighbourhoods together.

1.12 Key Conceptual Mechanisms

A considerable amount of literature has been published on criminology of place and has emphasized the concentrations and stability of crime over time in spatial units such as street segments and neighbourhoods. Despite these research efforts, the mechanisms driving neighbourhoods' crime co-movement have not been explored with methods that can accommodate assess the full range of potential dependencies between observational units. By using network theory, I think of the neighbourhood interdependencies in crime dynamics as a network, where

each neighbourhood is a node and the links between them represent co-movement of crime rates. Hence, in this section, I develop a conceptual framework to understand the structure of inter-neighbourhood connections and to explore the potential mechanisms (i.e., spatial dependence, non-spatial dependence (homophily), social frontiers, and people movement flows) drive neighbourhoods' crime co-movement.

(1) *Spatial dependence*. The spatial dependence might be defined in terms of geographical distance with the closest neighbourhoods having the strongest levels of co-dependence in terms of crime trajectories. The theoretical rationale for this approach is Tobler's First Law of Geography: "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This has been borne out in the crime distribution literature which has shown that contiguity/spatial proximity is a crucial factor in explaining crime distribution. Crime rates in one neighbourhood are influenced by crime rates in surrounding neighbourhoods (e.g., Morenoff et al., 2001, Zeoli et al., 2014). In particular, previous studies indicating that disadvantage in geographically proximate neighbourhoods affects—or at least is very significantly associated with—crime rates and victimization in proximate neighbourhoods (Morenoff et al., 2001, Peterson and Krivo, 2009, Peterson et al., 2010, Crowder and South, 2011, Vogel and South, 2016). These findings are also in line with a previous study showing that crime rates may be affected by poverty in proximate neighbourhoods (Graif and Matthews, 2017). Thus, in the Cleveland data, we expect crime co-movement links are more likely to be formed between proximate neighbourhoods.

(2) *Non-Spatial dependence (homophily)*. The question raised by the spatial dependence literature is why should crime rates of contiguous/proximate neighbourhoods move together? Why should Tobler's First Law of Geography apply to crime statistics? If we say that the reason is that neighbourhoods that are geographically close are more likely to be similar in terms of the drivers

of crime such as deprivation, social and racial diversity, then we are using spatial proximity/contiguity as a crude proxy for these underlying variables, whilst excluding the possibility that similar but distant neighbourhoods also have high levels of co-dependence in terms of their crime trajectories. Indeed, recent studies have argued that not only does spatial proximity promote criminogenic ties and the diffusion of crime, but that social proximity does so as well. Social ties are “spatially unbounded,” whereby individuals can be socially connected with others from distant areas through several channels (Wellman, 1999, Mears and Bhati, 2006), such as focal institutions or even the general propensity to associate with other people like themselves (Papachristos and Bastomski, 2018).

More recently, neighbourhood network research has examined the extent to which neighbourhood ties occur through spatial proximity versus other characteristics such as social proximity. As discussed earlier, the study of the co-offending networks in Maricopa County, by Schaefer (2012) found that social proximity contributes to the structure of criminogenic networks. In particular, he found that neighbourhoods with similar demographic characteristics are more likely to be connected and share co-offending ties. Another recent study by Papachristos and Bastomski (2018) examined how criminal co-offending connects different neighbourhoods in Chicago. The results confirmed the importance of spatial proximity in linking neighbourhoods. Nevertheless, co-offending ties were found commonly between neighbourhoods with similar social characteristics irrespective of the distance between them.

In the social network literature, the widely observed tendency for individuals to form ties with similar individuals (versus dissimilar individuals) is described as “assortative mixing” or “homophily”. The similarity can be defined by culture, race, gender, social background, similar life experiences and socioeconomic resources. McPherson et al. (2001) describe homophily as “the

principle that a contact between similar people occurs at a higher rate than among dissimilar people” (p. 416). This tendency towards homophily at the individual level increases the likelihood that friendships and criminal connections are more likely to emerge between similar neighbourhoods which are likely to have similar life experiences and social backgrounds for their respective residents.

Through the lens of homophily theory, I propose two possible complementary explanations for the co-movement of crime. The first is that neighbourhoods with similar underlying community structures and vulnerabilities may respond in similar ways to exogenous shocks causing crime rates to move in tandem. For example, if crime in neighbourhoods A and B is primarily caused by disadvantage, the national cuts in welfare spending may affect crime rates in both neighbourhoods in a similar way. Similarly, if the lack of resources and neighbourhood inequality are the causes of crimes in these neighbourhoods, the investment in the core community institutions that are necessary elements for the collective life may cause the similarity in the crime rates in these neighbourhoods. Thus, co-movements of crime may reflect deep underlying structural similarities between neighbourhoods.

The second explanation is that, as raised in chapter 2, there are networks of information that link the neighbourhoods through which innovation about crime, crime opportunities, trends in violence, etc. are transferred through information cascades (Pryce et al., 2018). These networks may be formed through crime families and gangs that have a presence in multiple neighbourhoods. There may be networks of connections between different crime gangs formed through alliances, common friendships, time in prison together, etc. They also are linked through school friendships, commuting flows, trade links in crime. Such networks are more likely to emerge between similar

neighbourhoods because “social networks tend to be homophilous” (McPherson et al., 2001, p. 416). Both of these theories, if true, would suggest systematic drivers of the co-movement of crime.

In summary, homophily means that nodes are more likely to be connected if they are similar. Thus, if neighbourhood A and B are said to be homophilous, it means that neighbourhoods A and B are more likely to be connected in terms of co-movement of crime if they have similar attributes.

(3) *Social frontiers*. In theories (1) and (2) above, the underlying conceptual driver of co-movements in crime between neighbourhoods is their similarity. However, there are reasons to believe that in some situations the opposite may be true; that contrasting neighbourhoods in close proximity may be more likely to experience inter-group conflict and this may cause a malignant connection to emerge between two adjacent neighbourhoods that drives co-movements in crime. This kind of contrast-connection could arise, for example, when an affluent neighbourhood is bordered by a deprived one. Relative deprivation theory (RDT) provides a potentially useful theoretical framework to understand the conflict that can arise from proximate inequality (Džuverovic, 2013). RDT focuses on the socio-psychological characteristics of individuals and emphasized the frustration they feel as a result of the difference between the actual and expected circumstances that become an essential motivation for violence (Dollard et al. 1939). According to RDT, a person or group's subjective dissatisfaction is caused by their relative position to another person or group's situation or position (Gurr, 1970). Relative deprivation is therefore present when a person or group lacks the resources to maintain the standard of living, activities, and luxuries to which they are accustomed or which are generally supported by the society to which they belong (Runciman, 1966). Due to the social pressure, individuals' tendency to continually compare their own situation with the situation or position of the rest of society increases if this is not attainable.

In order to address the overlooked spatial structure of economic inequalities in the segregation, Iyer and Pryce (2022) develop a theory of 'social frontier' as a conceptual foundation to understand the effect of spatial discontinuities between neighbouring communities. Iyer and Pryce (2022, p. 2) describe the social frontiers as “clear-cut boundaries with relatively high edge intensity in a particular socio-demographic dimension.” Hence, social frontiers present at the boundaries between neighbouring communities where the gradient in such dimensions rises or declines abruptly that ultimately affect the exacerbating territorial conflict and social tension.

Accordingly, contrasting neighbourhoods in other dimensions of residential mix may also be linked through social tensions, rivalry and territoriality. The relative deprivation literature (e.g., Džuverovic, 2013, Dollard et al. 1939, Kawachi et al., 1999) has long argued that inequalities in wealth and income can be a source of social tension and crime. However, this literature has often overlooked the spatial structure of economic inequalities, and how the impact of relative deprivation on crime may lead to particular types of inter-neighbourhood crime rate dependencies. Iyer and Pryce (2022) for example, have argued that marked relative deprivation between contiguous neighbourhoods could give rise to a type of “social frontier” which heightens territorial behaviour and inter-group conflict. As a result, we may see the opposite of a homophily effect where contiguous neighbourhoods with marked differences in affluence have similar crime dynamics due to this conflict. However, to my knowledge, this effect has yet to be studied empirically within the more capacious framework of network analysis.

Thus, I explore whether there is evidence of “social frontier” effects (Dean et al., 2019 ; Legewie, 2018; Legewie and Schaeffer, 2016)—i.e. whether crime rates are more likely to move together when contiguous neighbourhoods have sharply contrasting levels of disadvantage. It may be, for example, that when crime rates go up in a deprived neighbourhood, they also go up in a

neighbouring affluent neighbourhood which is a primary target of criminal activity. This may be because targeting well-healed addresses yields greater financial returns and/or because higher levels of relative deprivation invoke greater inter-group social tensions and resentment.

(4) *Movement flows*. Understanding the relationship between people movement flows across neighbourhood and the co-movement of violence is important for several reasons. First, higher movement flows among people travelling between two neighbourhoods are associated with increases in the potential of inter-neighbourhood social-tie formation (Sampson and Levy, 2020). A previous study in Chicago by Sampson (2012) provided evidence that social ties affect residential choices, because people seeking a home tend to move to a neighbourhood where they had prior social connections. Furthermore, prior research found that such social ties (1) require social interactions across neighbourhoods, a phenomenon that relies on the movement of information between neighbourhoods (Sampson and Levy, 2020) and (2) increase the likelihood of co-offending networks (Papachristos and Bastomski, 2018a, Schaefer, 2012). Second, this movement of people can shape the movement of information, attitudes, cultural practices, and beliefs across neighbourhoods, resulting in changes that are mirrored in the city as a whole (Sampson and Levy, 2020). By conceptualizing the city as a network of neighbourhoods, researchers can better understand the dynamics of violence and, in particular, how social issues (e.g., racial segregation, concentrated poverty) affect individuals' mobility and, in turn, may help to understand the co-movement of crime.

1.13 Conclusion

I have described the evolution of quantitative criminology from a focus on offender-focused drivers of crime, through to crim hotspots and neighbourhood analysis, through crime trajectories. I have also highlighted the main omissions in this nascent literature that have motivated the current

research, and summarised the main novelties and contributions of the work. The primary aim of this ‘three-paper’ thesis was to gain an understanding of the underlying factors that are associated with the crime co-movement of neighbourhoods. In chapter 2, using clustering analysis, I started the exploration of the interdependencies of crime dynamics between neighbourhoods and how these have implications for how we understand crime. For example, there appeared to be structural differences in the neighbourhood clusters membership and the determinants of crime between neighbourhoods with different crime trajectories. Whilst clustering neighbourhoods on the basis of similarity of crime trajectories, these clusters remain a ‘black box’ in the sense that the much of the underlying structures of interdependence remain hidden because we cannot observe the pairwise connections between neighbourhoods or analyse the factors that drive them – we can only observe and explain group-level connections between clusters of neighbourhoods. Thus, in chapters 3 and 4, I continued the investigation of neighbourhood interdependencies by exploring the structure of inter-neighbourhood linkages. I conceptualized the neighbourhood interdependencies in crime dynamics as a network, where each neighbourhood is a node and the links between them represent co-movement of crime rates. The focus of these chapters was on the structure and drivers of these interdependencies by examining the impact of (i) spatial proximity (ii) ‘social frontiers’ (ii) homophily—also known as ‘assortative mixing’— and (iv) people movement flows on the co-movement of crime. When combined, these mechanisms provide a comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in crime. This thesis broadly supports the development of the neighbourhood criminology literature that moved beyond a focus on the intra-neighbourhood settings to recognize the importance of inter-connected neighbourhoods. This also accords with the recent studies that

have argued that social proximity, as well as spatial proximity, promote criminogenic ties among neighbourhoods.

The headline findings of the research are summarised as follows:

1. Crime rates do not fluctuate in isolation, rather they are part of a complex web of spatial inter-dependencies.
2. The spatial distance is not adequate to explain the patterns of crime co-movement ties, other factors such as homophily are important for tie formation in the crime co-movement network.
3. The historical disadvantage and discrimination, captured through redlining maps from the 1930s, is a predictor of the co-movements of property crime across neighbourhoods today.
4. A ‘social frontier’ effect was found in the property crime co-movement network—that is crime rates in contiguous neighbourhoods are more likely to move in tandem when those neighbourhoods have sharply contrasting levels of disadvantage.
5. Neighbourhoods’ shooting incidents move together in part because they have similar composition, and in part because of the people movement flows that tie neighbourhoods together.

This thesis showed the added value that arises when considering spatial proximity, homophily, mobility flows, social frontiers, and the historical discrimination. In this regard, my overall research findings constitute evidence that the aforementioned factors may serve as underlying mechanisms that drive the co-movement of crime across neighbourhoods. In practice, this work provides a foundation for developing models that help us understand how crime cascades across neighbourhoods as discussed in detail in chapter 5. Furthermore, the novelty of this three-fold research approach to studying the co-movement of crime across neighbourhoods provided a

more coherent and comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in crime. Social-network analysis not only helped uncovering what conventional methods would have overlooked, but also identified potential underlying mechanisms driving the dynamics of crime across neighbourhoods. These mechanisms may very well cause neighbourhoods to experience similar trajectories of crime. Hence, at the policy level, developing the current approach and taking such mechanisms into consideration will more likely increase the efficiency of police intervention and the allocation of crime prevention resources.

CHAPTER 2

Data and Methods

2.1 Data

The analysis of this thesis relied on three types of data: crime data (i.e., property crime and shooting incidents), neighbourhood characteristics data, and people-mobility flows data

(1) *Property Crime data.* The property crime data employed in Chapter 2 and Chapter 3 were obtained from the Northeast Ohio Community and Neighbourhood Data for Organizing (NEOCANDO), an innovative data tool developed by the centre of Urban Poverty and Community Development at Case Western Reserve University. This tool allows academic researchers, community and economic development professionals, and public officials to pull information from a wide array of topic areas, all linked together by neighbourhood geography, all at no cost. This tool links data from local and federal sources at the census tract level through the county level, spanning topic areas from crime to demographic information on population and poverty. The property crime data were obtained at the census tract level for the years 2010–2017 and consist of the rate of property crimes (i.e., burglary, vehicle theft, arson, and larceny) per 1000 for each census tract.

(2) *The Shooting Incidents Data.* The shooting incidents data was obtained from the American Violence Project, a violence-data centre at New York University (americanviolence.org). The centre provides up-to-date city-level figures on murder rates in more than 90 of the largest 100 U.S. cities and features neighbourhood-level figures on violent crime in 30–50 cities. In collaboration with Professor Patrick Sharkey scientific director of the American

Violence Project, I obtained the Chicago shooting incidents data at the census tract level for the period between 2014 and 2020. Each observation represents one shooting incident with several variables such as date and census tract number. The challenge was that shooting is a rare event compared to aggregate crime incidents. Thus, aggregating the shooting incidents into short time frames, such as weekly or monthly, shows some noise. Therefore, shooting incidents were aggregated at annual level to avoid such noise. Another challenge was that the shooting incidents data were collected for 804 census tracts and the spatial data (the census tract shapefile) included 780 census tracts. Therefore, the tracts that are not in the shapefile were excluded due to insufficient spatial data.

(3) *Neighbourhood Characteristics*. One of the purposes of this thesis is to explore the potential mechanisms that drive the similarity of the crime trajectories. Specifically, to explore the similarity effect (i.e., homophily) as a potential mechanism and whether there are a relationship between the similarity of two neighbourhoods in terms of some important characteristic (e.g., poverty rates, age groups, racial composition, etc) and likelihood of being connected in terms of co-movements of crime. Thus, several measures of neighbourhood characteristics were obtained from 2010 US census data. The American Community Survey (ACS) is a continuous survey that offers data for all of the different geographical areas, all the way down to the block group level. This provides communities with the up-to-date information they require in order to plan investments and services. The American Community Survey (ACS) examines a wide variety of subjects, including the social, economic, demographic, and housing characteristics of the people in the United States.

Although the ACS offers extensive data at neighbourhood level, there are some limitations in the data. For example, data related to schools, community centres, parks, offenders, and public

transportation is not available. Therefore, being dependent on ACS, I could not measure all the theory related variables, and this is an important limitation of this thesis, as discussed more in the conclusion. Also, one of the challenges in the data preparation stage was related to the historical redlining maps. The thesis explores the impact of historical discrimination (1930s redlining maps) as one of the homophily measures. The challenge was that the redlining maps were in the 1930s and the Cleveland spatial data used in this thesis was in 2010 (i.e., the 2010 census tracts shapefile); and the census tract boundaries changed over time. Therefore, I used the 1930 redlined neighbourhoods' coordinates and relocated them within the 2010 census tract boundaries as shown in Chapter 4.

(4) *People-mobility-data*. people-mobility flows obtained from SafeGraph (SafeGraph.com), which are calculated on the basis of millions of anonymous mobile phone users' visit trajectories to various places. The mobility data was computed, aggregated, and inferred the daily dynamic origin-to-destination (O-D) population flows at the census-tract level, and then trimmed the flows down to pairs consisting of at least 10 daily trips on average. I got the access to one dataset for data that were aggregated for 2019, which served as the annual base.

2.2 Methods

2.2.1 Crime Trajectory Clustering

A considerable amount of literature has been published on the criminology of place at different geographic units, including street segments and intersections (Weisburd et al., 2012). Prior research examining geographical crime concentration has confirmed the existence of a clear spatial crime concentration at micro locations, with a high degree of stability over time.

Previous research has used different clustering methods to determine the geographic units that experienced similar crime trajectories. Crime trajectory analysis has employed a methodology known as Group-Based Trajectory Model (GBTM), that was initially developed to study the pattern of offending behaviour, as well as the trajectories of offenders (Nagin and Land, 1993; Nagin, 1999; Nagin and Nagin, 2005). GBTM has been one of the most commonly used methods of trajectory analysis. This method assumes that observations are composed of fixed (but unknown) groups, each with a distinct underlying trajectory. The main task of this model is to identify a number of groups containing individuals following similar trajectories over time, in order to examine the progression of individuals and estimate the impact of covariates on group membership and their trajectory.

GBTM originated in the field of development criminology, being employed by (Nagin and Land (1993) to investigate the trajectory of juvenile offenders and identify sub-groups of criminal behaviour. Formally, the model defines that the population is divided into groups with different developmental trajectories. Each group's offending trajectory is described by a different set of characteristics that can vary freely. This sort of model produces the trajectory parameters for each group, the proportion of the population in each group, and the posterior probability of belonging to a certain group for each sample member. After estimating a model's posterior probability, individuals can be assigned to a group based on their greatest likelihood.

While this method isn't as efficient as linear growth models, it does allow for more varied and interesting behaviour over time (Groff et al, 2010). Since not everyone engages in criminal behaviour and people appear to begin and end their involvement at vastly different ages, there is widespread consensus that delinquency and crime are situations in which this group-based trajectory approach could be appropriate (Nagin 1999, 2005; Raudenbush 2001). Since we do not

have a firm hypothesis about the fundamental trend, the group-based trajectory approach seems like a good bet for spotting important shifts in our data.

There are two software packages that can estimate group-based trajectories: Mplus, which is a proprietary package, and Proc Traj, which is a special SAS procedure that the National Consortium on Violence Research makes available for free (for a detailed discussion of Proc Traj, see Jones et al. 2001). When estimating the trajectories of data with Proc Traj, there are three options: the parametric form (Poisson, normal, or logit), the functional form of the trajectory over time (linear, quadratic, or cubic), and the number of groups. Due to the high level of complexity of these models, the researchers run the risk of arriving at a local maximum or peak in the likelihood function, which is a less ideal solution (Groff et al., 2010). When selecting a model, it is important to take into consideration how stable the result remains when using a variety of different beginning value combinations. In the end, the usefulness of the groups is defined by their capacity to distinguish between different trajectories, the number of units that are included in each group, and the degree to which they are similar to one another (Nagin 2005).

Weisburd et al., (2004) were the first to use GBTM in the literature of crime and place (Curman et al., 2015; Anderson et al., 2016). Their study aimed to determine whether sub-groups of geographic units (e.g., street blocks) evidenced similar patterns of crime trajectories over time as those of individual criminal careers. Weisburd et al. (2004) utilized the data of street crimes between 1989 and 2002 in Seattle, Washington, and were able to identify eighteen unique trajectory groups following similar crime trajectories at the street segment level. Following Weisburd et al. (2004), a considerable amount of literature has examined the crime trajectory at micro places (i.e. street segments and intersections) revealing a considerable concentration of crime and stability over time.

Alternatively, using a multilevel negative binomial regression model, Braga et al (2010) analysed records of Assault and Battery by Means of a Deadly Weapon— Firearm (ABDW— Firearm) incidents in the city of Boston, USA for the period between January 1980 and December 2008. Specifically, they developed individual growth curve models in order to evaluate the changes in the ABDW-Firearm events at the street unit level that occurred throughout the observation period. Braga et al. (2010) used the negative binomial models for two main reasons. First, the main goal was not to cluster the street units into groups or classes. Instead, their research sought to examine how the leading edge of firearm trends in Boston is affected by the specific trends of each geographic unit. In other words, growth curve models make it possible to fully describe the temporal order of each unit over the entire time period. Thus, instead of putting each street unit into a group, they wanted to look at each slope over the time period. Their findings demonstrate that breaking units into quartiles of slopes is an effective way to display data aesthetically and empirically without distorting the actual value assigned to each unit. Second, the data contains many street units with only one observation point. This suggests that a large number of street units don't really have a "trend," but instead experience a single event. Because of this, they only included the street units that had more than one event in the analysis. The results demonstrated that, during the study period, gun violence in street segments generally followed two trajectories: a volatile trajectory or a stable trajectory. They found that the volatile group included 3% of the street segments and intersections responsible for more than 50% of violent crimes, including the use of guns. Similar to Weisburd et al. (2004), Braga, Papachristos and Hureau (2010) found that a small group of street segments and intersections were responsible for changes in trends of violence citywide over time. In a subsequent study, Braga, Hureau and Papachristos (2011) studied robberies in the same city over the same period, with similar results, i.e., a small group of micro

locations were found to be the primary drivers of the overall changes in the number of robberies in the city during the study period.

In addition, in a recent article, Curman et al. (2015) used an alternative method to study crime trajectories in Vancouver, Canada. They used the K-means method to explore and cluster the crime trajectories of the street segments in the city of Vancouver over a 16-year period (1991-2006). K-means is a non-parametric clustering method originally developed by Calinski and Harabasz (1974) that aims to identify clusters of observations that share similar traits. The K-means statistical technique has been used in the criminology literature since Huizinga et al. (1991) used the K-means algorithm to cluster the offending trends of youth over two years (1987-1988). Another implementation of K-means in the crime literature was by Mowder et al. (2010), who used the K-means algorithm to study the resilience of male and female offenders in a juvenile facility. Curman et al. (2015) examined the trajectories of individual types of crime, as well as total crimes, for a period of sixteen years (i.e., between 1991 and 2006). The city of Vancouver experienced a drop in crime of approximately 41% during the study period. Although the K-means clustering affected the results by reducing the number of clusters, both methods led to similar results in that only a small fraction of street segments contributed to the overall crime reduction.

In Chapter 3, the annual property crime rate and the k-means algorithm were therefore employed to identify clusters of neighbourhoods experiencing similar crime trajectories over time. Hence, following the estimation of the rate of change using simple regression, the estimated coefficients were used to cluster these trajectories using the k-means algorithm. The k-means clustering algorithm (Forgy, 1965; MacQueen, 1967; Hartigan and Wong, 1979) has been one of the most popular tools for clustering data. One of the challenging problems in clustering analysis is choosing an optimal number of clusters before fitting. There are several methods that can be

used to find the optimal number of clusters, such as the elbow method, which was chosen in this study. The elbow method is one of the most popular methods used for determining the optimal number of clusters in a data set (Andrew, 2012). The elbow plot visualizes the total within-cluster sum-of-squares against K (i.e., the number of clusters). The idea is that the sum of square values starts very high when $k = 1$ and then decreases as the number of clusters increases. At some point, the value will drop dramatically at a specific k value. After that, it reaches a plateau and then decreases very slowly when we increase it further. This is the point we look for, which indicates the optimal number of clusters (Kodinariya and Makwana, 2013; Bholowalia and Kumar, 2014). However, in this analysis, the purpose of using k-means is to determine the main reprehensive trajectories that represent the main crime trajectories in the city. Thus, I started the clustering analysis with two clusters, with the number of clusters incrementally increased until I found the representative and distinctive trajectories at three clusters (Cluster 1: the increasing group; Cluster 2: the decreasing group; and Cluster 3: the stable group). That is, from the fourth cluster onwards, the trajectories of the three clusters are similar to the first three clusters (i.e., the trajectory of cluster 4 onwards is another increasing, decreasing, or stable trajectory). Thus, three trajectory clusters were identified by using the k-means clustering method, representing the distinctive trajectories in all neighbourhoods over the period of study. The neighbourhoods were divided into three main crime trajectory groups: Group 1: the increasing group; Group 2: the decreasing group; and Group 3: the stable group.

The K-means algorithm was used in the clustering analysis as an alternative method to other clustering methods such as GBTM that have been widely used in trajectory clustering. Using K-means was useful in three ways. First, K-means does not require the data to be in a specific distribution and beats the GBTM in Proc Traj in accommodating larger data (Curman et al. 2015).

Second, the GBTM produces a large number of clusters compared to k-means, which makes the analysis and interpretation more complicated in the second stage (i.e., the group membership drivers using multinomial logistic regression where all clusters will be compared to one reference cluster). This complexity is explained in Chapter 2. Third, the K-means statistic is available in most of the statistical analysis tools while the GBTM is limited to paid tools.

2.2.2 Neighbourhood' Networks and Crime

There has been growing awareness of the need to move beyond the focus on intra-neighbourhood dynamics, to recognize interdependence of neighbourhoods (Peterson and Krivo, 2009, Tita and Greenbaum, 2009). Quite a few empirical studies have tried to study such interdependence by exploring the mechanisms that link neighbourhoods to one another and that determine the structure of crime diffusion. During the last twenty years, research has provided evidence that crime diffusion surpasses neighbourhood boundaries (Anselin et al., 2000, Anselin, 2002, Graif et al., 2014, Morenoff et al., 2001, Peterson and Krivo, 2010). For example, pouring over homicide data that covered a twenty-year period in Newark, New Jersey, Zeoli et al. (2014) found evidence of a stable spatiotemporal diffusion process, where rising rates of homicides were emerging in the city centre at the start of the twenty-year period and then disseminated southward and westward during the subsequent two decades. The impact of spatial proximity is a robust finding in the crime-diffusion research at various levels of geographic aggregation.

When we consider the mechanisms that drive the diffusion of crime, a question arises regarding the extent to which the diffusion occurs because of spatial proximity rather than because of other characteristics such as social proximity. Conceptually, scholars have argued that not only does spatial proximity promote criminogenic ties and the diffusion of crime, but social proximity does so, as well. Social ties are “spatially unbounded”; that is, individuals—through several

channels—can be socially connected with others from geographically distant areas (Wellman, 1999a, Mears and Bhati, 2006).

Recent empirical studies support this perspective. Using social network analysis and exponential random graph models (ERGMs). The Exponential family is a family of statistical models for many types of data and the Exponential random graph models (ERGMs) is a statistical model for analysing social network. In social network analysis, there are several metrics and measurements exist to describe the structure of an observed network like density, betweenness, centrality, etc. These metrics, however, characterise the observed network, which is just one of many possible alternative networks. The structural properties of this group of alternative networks may be similar or dissimilar. In other words, the observed network is thought to be one of many possible networks formed by an unknown stochastic process that models potential network links as a random variable (Wasserman and Pattison 1996). Thus, the aim of an ERGM is to examine the factors that influence tie formation between nodes. Thus, ERGM provide a model for statistical inference for network structure and the processes influencing the existence (and absence) of network ties. The model takes the network as a graph constituted by nodes and edges (ties) between nodes and examine the factors that influence ties formation between nodes. Thus, due to the relational nature of network data, ERGM violates the assumptions of independence of standard statistical models such as linear regression. Such models assume that each unit of observation in the data (in this case, neighbourhoods) is independent from all others. The conditional independence assumption is clearly problematic if we are interested in what determines the inter-neighbourhood dependence of crime dynamics as it precludes the very phenomenon we are seeking to study. ERGMs are theory driven so researchers needs to consider the complex theoretical reasons for the emergence of social links in the observed network.

For example, Schaefer (2012) studied youth co-offending networks in Maricopa County, Arizona. Specifically, all youth offenders were assigned to a certain census tract based on their residential address at the time of their arrest. A two-mode, tract by offence matrix was constructed by aggregating the data inside each tract to find cross-tract relations. The number of youth in tract i who engaged in offence j was recorded in each cell of the matrix. The binary partition was performed using a symmetric, tract-by-tract matrix, which was calculated by multiplying the original matrix by its transpose. Cells in the matrix would be filled in according to whether or not a youth from tract i committed a crime with a youth from tract j . In the sample, juveniles frequently commit offences that occur in multiple jurisdictions. There was significant variation in youth co-offense between census tracts (72%) as evidenced by the 3058 youth co-offense associations. In order to test the interdependencies between tracts, a set of ERGMs were estimate. While accounting for co-offending tendencies at the tract level and other variables indicating network structure, a number of ERGM models were estimated to assess the relational processes expected to connect tracts together, such as social distance and spatial closeness.

Schaefer (2012) uncovered evidence that social proximity contributes to the structure of criminogenic networks. More specifically, he found that neighbourhoods with similar demographic characteristics are more likely to be connected and to share co-offending ties than are demographically disparate neighbourhoods. Similarly, a recent study by Papachristos and Bastomski (2018b) examined how criminal co-offending forges connections between various neighbourhoods in Chicago. The results confirm that spatial proximity is important for the phenomenon of linked neighbourhoods. The results also confirm that co-offending ties were common between socially similar neighbourhoods, irrespective of the distance between them.

Some research has employed various forms of regression analysis to investigate inter-neighbourhood crime dynamics. For example, Mears and Bhati (2006) have used negative binomial regression to examine the impact of both social and spatial proximity on homicide counts. They drew on homicide counts data in Chicago's communities or cluster of neighbourhoods between 1989 to 1991. Their findings show that resource deprivation in one area has an impact on the homicide rates in distant and socially similar areas. This methodological approach is not appropriate for network analysis because it rests on the assumption that observations are either conditionally or unconditionally independent of one another (Contractor, Wasserman and Faust, 2006; Harris, 2014). This assumption makes regression analysis less than ideal, to say the least, if the very purpose of the analysis is to estimate the degree of dependence between neighbourhoods (Dean and Pryce, 2017). Spatial econometric methods such as exploratory spatial data analysis and spatial regression models (Anselin et al. 2000) relax this assumption but in a very specific and limited way; for example, the methods allow for dependence between neighbourhoods that are contiguous or in close proximity. Distant neighbourhoods are assumed to be unconnected to one another. The standard spatial regressions are methodologically useful and used widely to study the crime diffusion and clusters (e.g., Mearns and Bhati, 2006; Tita and Radil, 2010a, 2011). However, such models are imprecise to study the interdependency between neighbourhoods as "they model the diffusion of crime as if it spreads like an airborne pathogen" (Papachristos and Bastomski, 2018a). Furthermore, the standard spatial regressions are useful in simply demonstrating and mapping the crime patterns more than explaining the causes of the crime clusters (Radil et al., 2010). Thus, relying on such models is considerably imprecise to explain the complicated intercommunity social processes driving crime patterns (Leenders, 2002). Therefore, if we want to understand how, in crime dynamics, inter-neighbourhood linkages might emanate from a range

of factors that go beyond the distance and contiguity factors, then we need to employ methods designed specifically for the analysis of networks. However, as far as I am aware, network methods have yet to be applied in the literature on crime dynamics.

2.2.3 Building Neighbourhoods' Crime Networks

Building on the prior neighbourhood network research, in this thesis, I investigate the neighbourhood interdependencies by exploring the structure of these inter-neighbourhood linkages. We can think of the neighbourhood interdependencies in crime dynamics as a network, where each neighbourhood is a node and the links between them represent co-movement of crime rates. My interest in this thesis is in the structure and drivers of these interdependencies. For example, is there evidence of homophily—also known as ‘assortative mixing’—in the co-movement of crime? In other words, are neighbourhoods that are similar in terms of their characteristics such as the levels of poverty and ethnic mix more likely to have closely entwined crime trajectories? I am also interested in the role of geographical proximity: to what extent do neighbourhoods that are neighbourhoods together have crime rates that move together, and is there evidence of ‘social frontiers’ in crime? That is, will adjacent neighbourhoods with contrasting levels of affluence actually be more likely to have crime rates that move together because of the social conflict between such neighbourhoods?

In this analysis, a network of neighbourhoods is defined by the co-movement of crime. Neighbourhood A and B are said to be linked if there is a relationship between their crime trajectories. Various ways could be used to test this relationship such as the correlation matrix or the cointegration test (Dean and Pryce, 2018). The network therefore consists of nodes (neighbourhoods) and the edges which link them. A link is said to occur between 2 nodes if there is a high correlation over time in their crime rate dynamics as shown in Figure 1 and Figure 2.

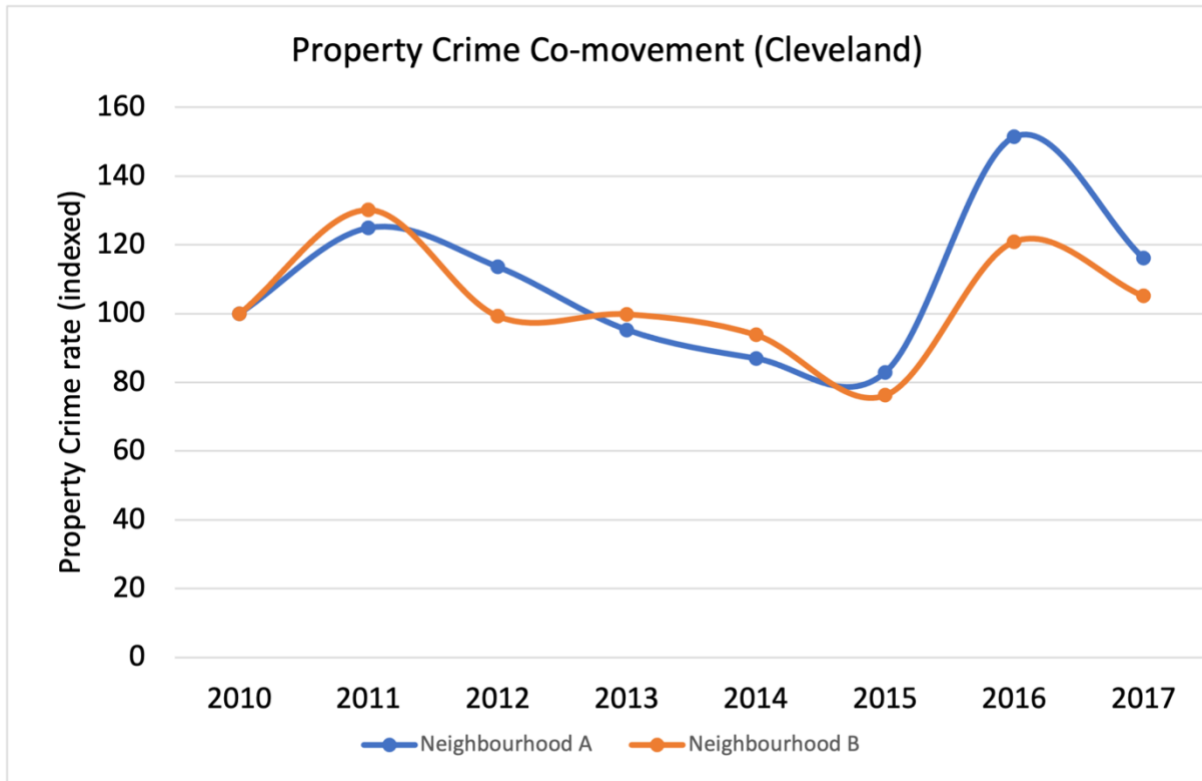


Figure 1 An example of Neighbourhoods Property Crime Co-movement in Cleveland

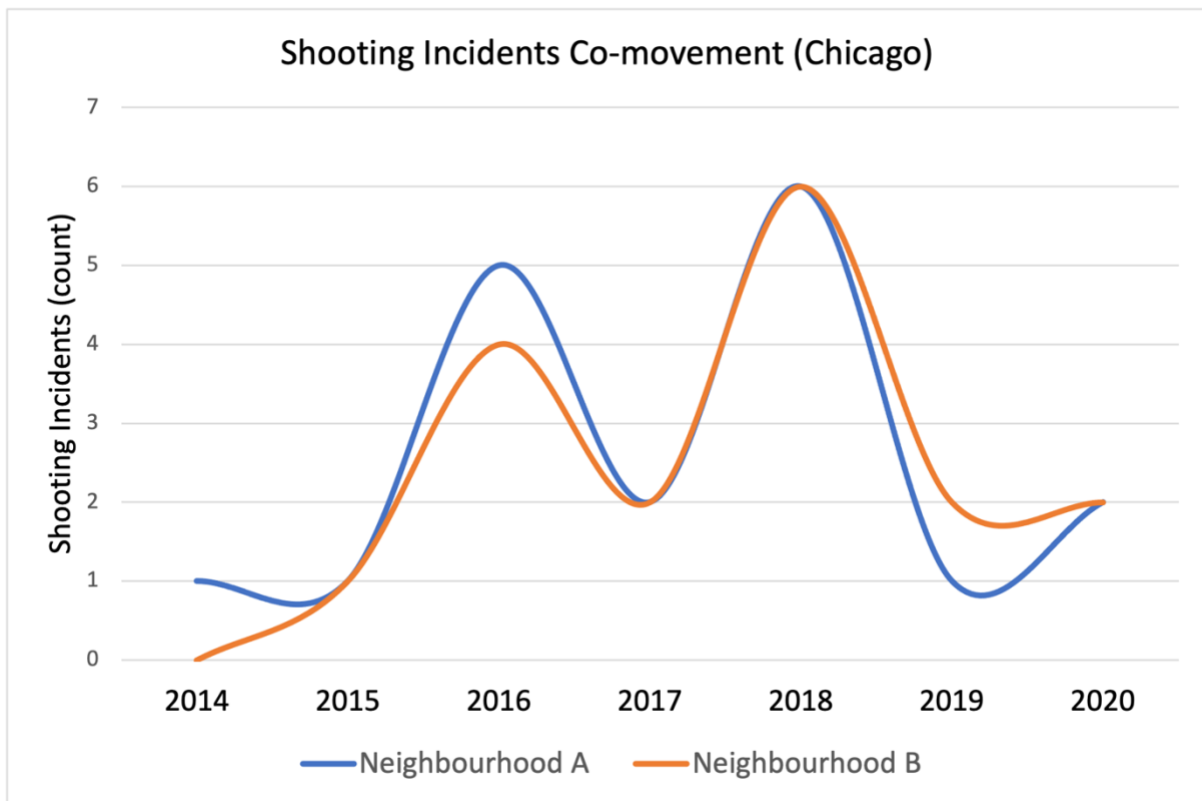


Figure 2 An example of Neighbourhoods Shooting Incidents Co-movement in Chicago

Let $G(V,E)$ be an undirected network, where V is the set of neighbourhoods in the city and E is the set of edges. The links between neighbourhoods can be summarized using an adjacency matrix, C , the elements of which represent the pairwise crime trajectory correlation between i and j . An edge between two nodes i and j exist if the crime rate of neighbourhoods i and j move together (i.e., crime co-movement). The measure of the crime co-movement is denoted C_{ij} , so that an edge is said to exist between i and j if C_{ij} is greater than N , where N is the threshold for the correlation of crime rates. The threshold selection was based the stability of model results (i.e., stability of variable coefficients). Hence, the threshold selection began from a base threshold of 0.50, with the value of correlation incrementally increased until the best fitting model was found. The model results show stability in the range of 0.50-0.65 and threshold 0.65 was selected to build Cleveland's network. Similarly, in Chicago's shooting dynamic network, the stability was achieved in the 0.50–0.90 range, and the threshold of 0.90 was selected to build the network.

2.2.4 Summary

Prior research into neighbourhood networks has largely focused on co-offending and gang networks rather than neighbourhood-level crime trajectories. This is because of the way they used to build the neighbourhood network. That is, in the co-offending network, an edge between two neighbourhoods i and j formed if a youth from tract i commits a crime with a youth from tract j . However, in the neighbourhood crime dynamics, there is no direct approach to building the network. An innovative idea, therefore, is required to think of the neighbourhood crime dynamics as a type of network. Thus, in this thesis, I developed an idea to explore the comovement of neighbourhood crime trajectories as a network where each neighbourhood is a node and the links between them represent the co-movement of crime trajectories.

Therefore, conceptualizing the co-movement of crime as a type of network has three key advantages: (i) it provides a more coherent and comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in crime; (ii) it provides a more appropriate empirical framework for analysis that is not constrained by the prohibitive assumptions of node independence assumed in traditional regression analysis; and (iii) it provides insights into the mechanisms linking similar neighbourhoods to one another. Also, this thesis showed the added value that arises when one considers homophily, mobility flows, social frontiers, and the historical discrimination of redlining maps (explained in chapters 3 and 4). In this regard, my overall research findings show that the aforementioned factors may serve as underlying mechanisms that drive the co-movement of crime across neighbourhoods.

2.3 Exploratory Analysis

Two US cities were included in this thesis Cleveland and Chicago.

2.3.1 Cleveland

This study utilises data on Cleveland, the second largest city in the state of Ohio. It is located in north eastern Ohio, at the mouth of the Cuyahoga River. The study location was chosen for the following reason. Cleveland, OH is an American standard city that has a population of 383,793. However, in 2017, the crime rate for the city was 786 crime per 100,000 people, which is 2.8 times greater than the national average and higher than 98% of US cities (City-data.com, 2017). Hence, the fact of it being a high-crime city as well as the availability of crime data motivate a more in-depth investigation of how Cleveland crime rates move over time. According to the Census Bureau QuickFacts (2017), the racial composition of Cleveland was as follows: around

50% of Cleveland residents are Black or African Americans, 40% are White, with the remainder of mixed or other racial heritage.

Cleveland's property crime data employed in this thesis were obtained from the Northeast Ohio Community and Neighbourhood Data for Organizing (NEOCANDO), an innovative data tool developed by the centre of Urban Poverty and Community Development at Case Western Reserve University. The data were obtained at census tract level for years 2010-2017 and consist of the rate of property crimes (i.e., burglary, vehicle theft, arson, and larceny) per 1000 for each census tract. There were 175 census tracts in the city of Cleveland (169 included in the analysis following the exclusion of outliers).

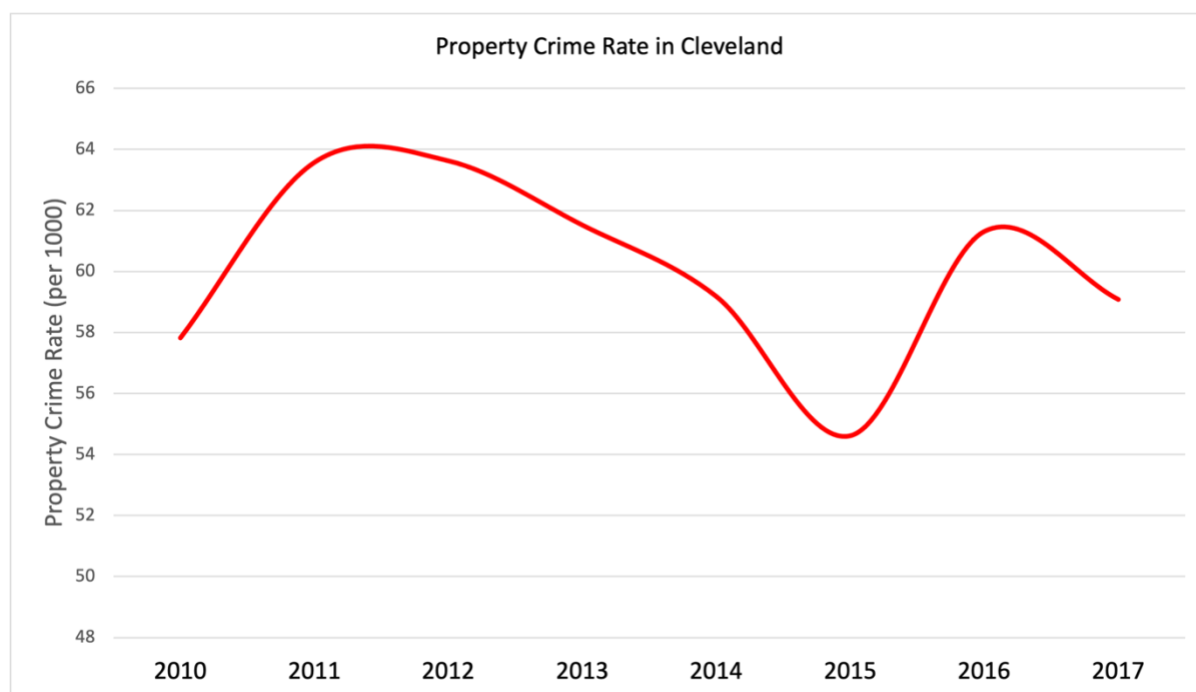


Figure 3 Property Crime Rate in Cleveland 2010 - 2017

Figure 3 shows an overview of the property crime trajectory in the city of Cleveland over the study period. Property crime has increased by 3% over the period between 2010 and 2017.

From the graph above, we can see that Cleveland did not experience a major change in the property crime rate over the study period. However, the citywide crime trajectory does not reflect the precise crime changes occurring in the city on a smaller geographic scale, such as neighbourhood. As shown in Figure 3, the results of neighbourhood crime trajectory clustering (detailed analysis presented in Chapter 2) show that some neighbourhoods experienced over a 40% increase in the property crime rate over the study period. Also, some neighbourhoods demonstrated a 22 % decrease in property crime rates over the study period.

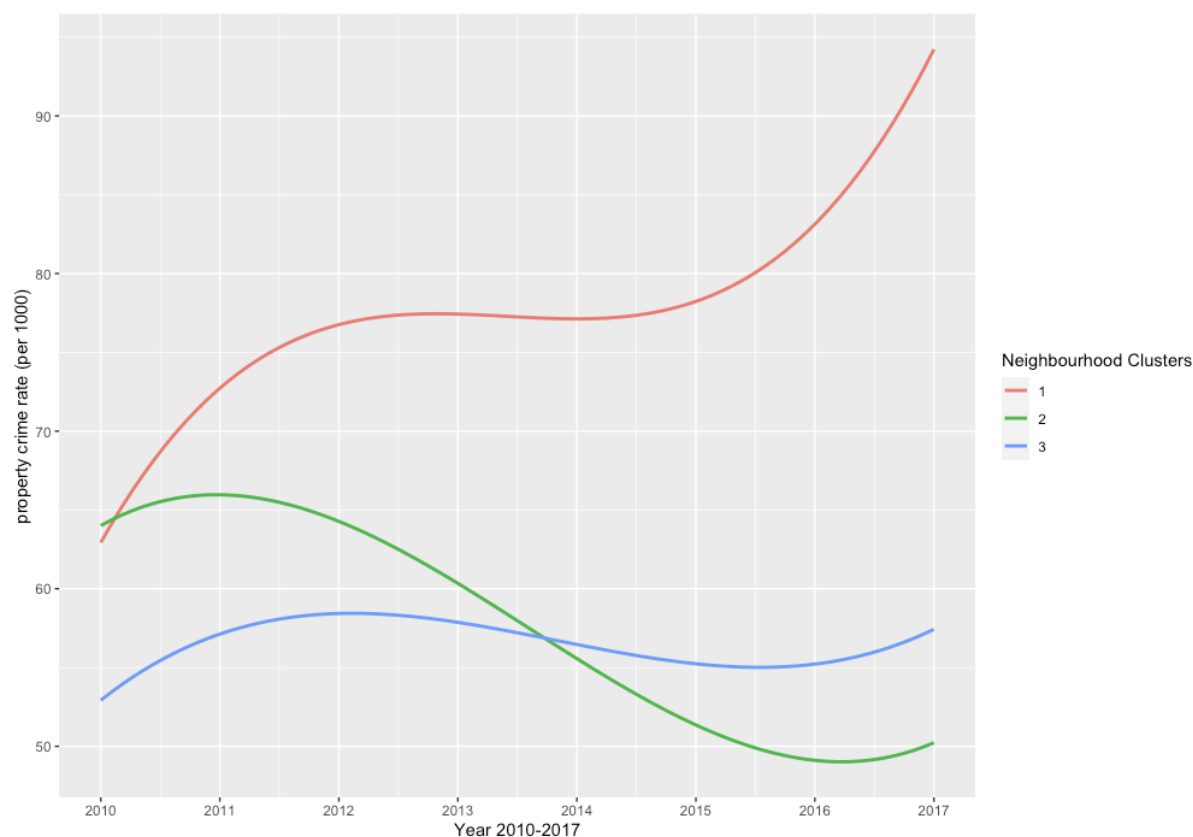


Figure 4 Results from clustering the crime trajectories representing the distinctive

In chapter 4, I continue the investigation of the interdependencies of the property crime trajectories in Cleveland's neighbourhoods by exploring the structure of these inter-neighbourhood

linkages. We can think of the neighbourhood interdependencies in crime dynamics as a network, where each neighbourhood is a node and the links between them represent co-movement of crime rates. My interest in chapter 3 is in the structure and drivers of these interdependencies. For example, is there evidence of homophily—also known as ‘assortative mixing’—in the co-movement of crime? In other words, are neighbourhoods that are similar in terms of their characteristics such as the levels of poverty and ethnic mix more likely to have closely entwined crime trajectories? This could be important in terms of predicting how changes to neighbourhood characteristics might affect future crime trajectories. I am also interested in the role of geographical proximity: to what extent do neighbourhoods that are neighbourhoods together have crime rates that move together.

Figure 5 displays Cleveland’s neighbourhood crime co-movement network. Nodes represent the 169 neighbourhoods in the city, and the edges that link them represent the co-movement of property crime trajectories between neighbourhoods. That is, an edge exists between two nodes (neighbourhoods) which means that the crime trajectories of these two neighbourhoods move in tandem during the study period from 2010 to 2017. The edge density of Cleveland’s network is 0.08, which indicates the proportion of edges in the network (1204 edges) over all possible edges that could exist.

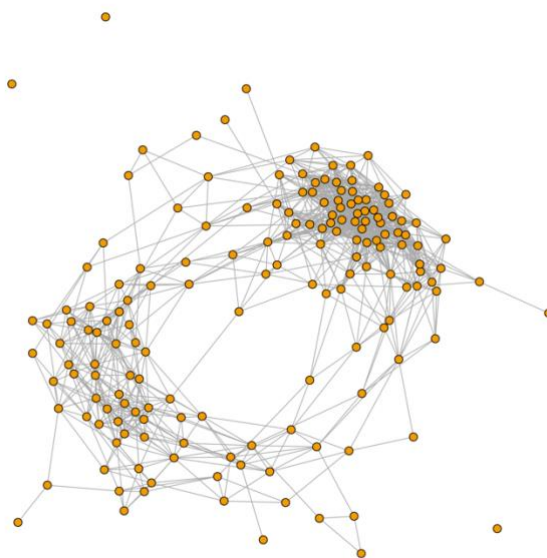


Figure 5 Cleveland Neighbourhood Crime Co-movement Network, N=169

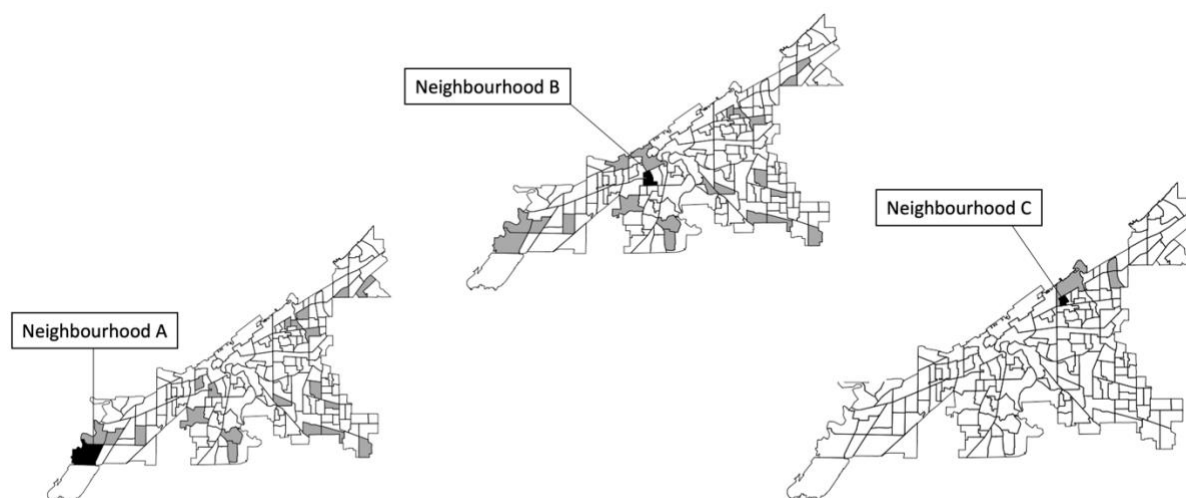


Figure 6 Ego networks for neighborhoods that their crime co-movement ties reach to the largest average, the average, and the smallest average distance across the city.

Simply visualizing crime co-movement ties between neighbourhoods masks the long reach of ties that extend beyond geographically proximate neighbourhoods and, in so doing, ignores how far any single neighbourhood's ties reach across the city. As an example of how any particular neighbourhood's pattern of ties may or may not extend beyond local geography, consider Figure 6 which represents the ego networks of crime co-movement ties for three different neighbourhoods. The term "ego network" here refers to each neighbourhood's spatial patterning of co-movement ties—that is, those neighbourhoods (alters) to which the focal neighbourhood ("ego") is directly connected and the ties among those alters. These three maps show the ego networks of neighbourhoods where ties reach to (A) the largest average distance across the city, (B) the average distance, and (C) the smallest average distance.

As the map shows, neighbourhood A has ties (i.e., crime co-movement ties) with 20 other neighbourhoods in the city, most of which are geographically distant. The average distance between neighbourhoods in the network is 5.31 miles. Neighbourhood A has the largest average

distance, at 10.11 miles, that is, neighbourhood A has ties with neighbourhoods that are 10.11 miles apart. Neighbourhood B has connections with 21 other neighbourhoods across the city. Similar to neighbourhood A, most of those connections are with geographically distant neighbourhoods. Neighbourhood's B ties traverse an average of 5.31 miles. Finally, neighbourhood C has links to three different neighbourhoods; one is adjacent and the other two are proximate. Neighbourhood C's ties traverse the smallest average geographic distance, at 2 miles.

Although this descriptive analysis shows only three neighbourhoods out of 169, the purpose of these ego-network descriptive maps was to emphasize that neighbourhood networks are not always a function of geographical proximity and have undermine the reliance on simple formulations of spatial dependence assumed in some econometric models. As shown in Figure 4, most of the three neighbourhoods' ties are to distant neighbourhoods across the city. So, these results show that the spatial distance alone is insufficient to explain the crime co-movement ties and raises the question of what other factors contribute to the formation of crime co-movement network. A detailed investigation to explore this question is presented in Chapter 3.

2.3.2 Chicago

This study uses the shooting incidents data on the city of Chicago. I obtained the shooting-incident data from the American Violence Project, a violence-data centre located at New York University (americanviolence.org). The data cover the annual shooting incidents in each census tract (i.e., neighbourhood) in Chicago for the period between 2014 and 2020. For the city of Chicago, there are 833 census tracts, 731 of which were included in the present study (with the remainder excluded owing to their insufficient data).

Chicago is the largest city in the state of Illinois and the third most populous city in the United States with over 2.7 million residents. Chicago has been known for its high rate of violence for many decades and “used to making the national news for violence.” The city features racial, ethical, and income segregation (Sharkey and Marsteller, 2022) and was labelled the “murder capital” of the United States (Huq and Rappaport, 2022). Thus, since Shaw and McKay (1942), Chicago has been the study area for many groundbreaking theories such as community social processes and violence (Sampson, 2012), and the transformation of urban poverty (Wilson, 1987). Thus, Chicago was selected to build on the decades of research conducted in Chicago. According to the Census Bureau (2020), the racial composition of Chicago was as follows: Black or African American: 28%, white: 33%, Hispanic or Latino: 28%, and other races: 11%.

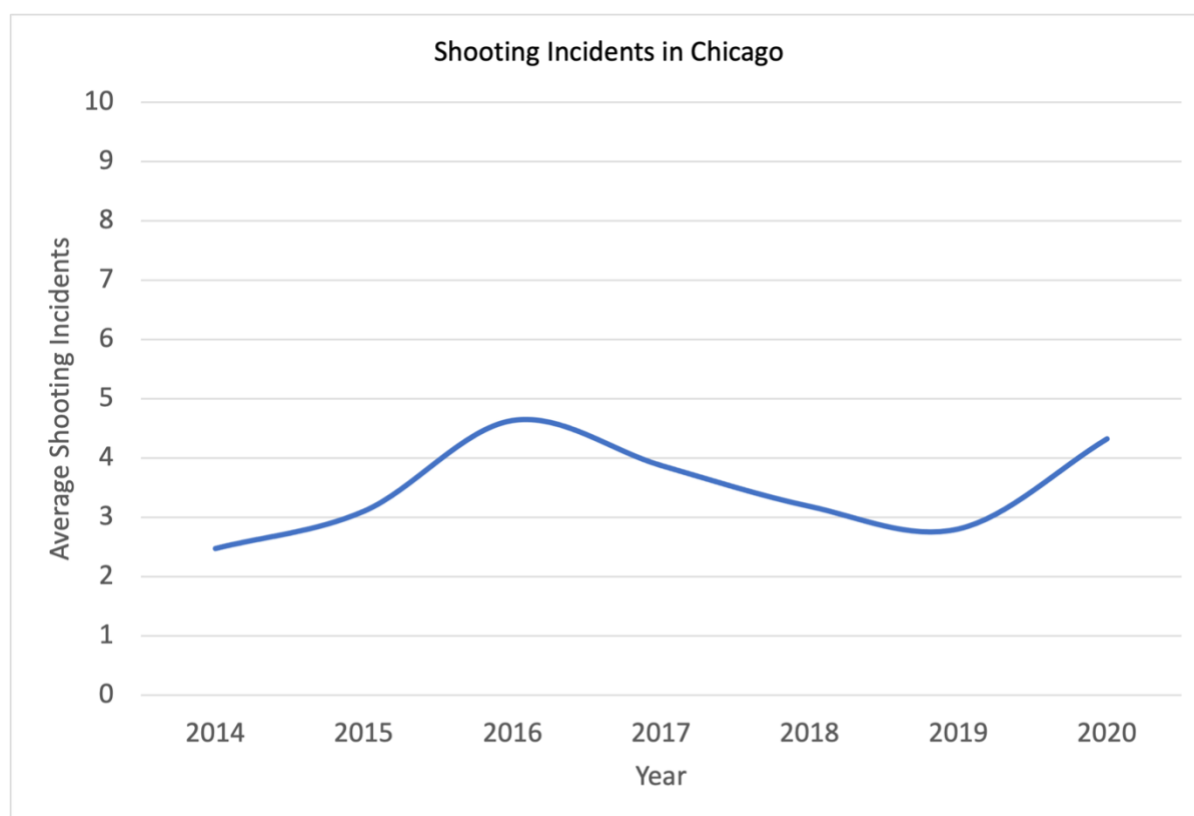


Figure 7 Annual Shooting Incidents in Chicago 2014 - 2020

Chicago experienced about a 70% increase in the average shooting incidents between 2014 and 2020. However, similar to Cleveland, looking at the city-wide trajectory does not reflect the precise patterns for all neighbourhoods in the city. Both racial segregation (Morenoff et al., 2001) and poverty (Sharkey and Marsteller, 2022) exist in many Chicago neighbourhoods, and racial segregation, in particular, is strongly associated with the incidence of crime. Peterson and Krivo (2010) observed just such an association between inequality and violence rates, where violence rates in predominantly black neighbourhoods were 327% higher than in predominantly white neighbourhoods. Sharkey (2014) found that socioeconomic disadvantage was concentrated in 87% of black neighbourhoods. In contrast, only 15% of the white neighbourhoods suffered from local or proximate disadvantage. The current shooting data, as shown in Figure 8, illustrates that high-poverty neighbourhoods experienced higher shooting incidents compared to the city-wide rate and lower-poverty neighbourhoods in all years.

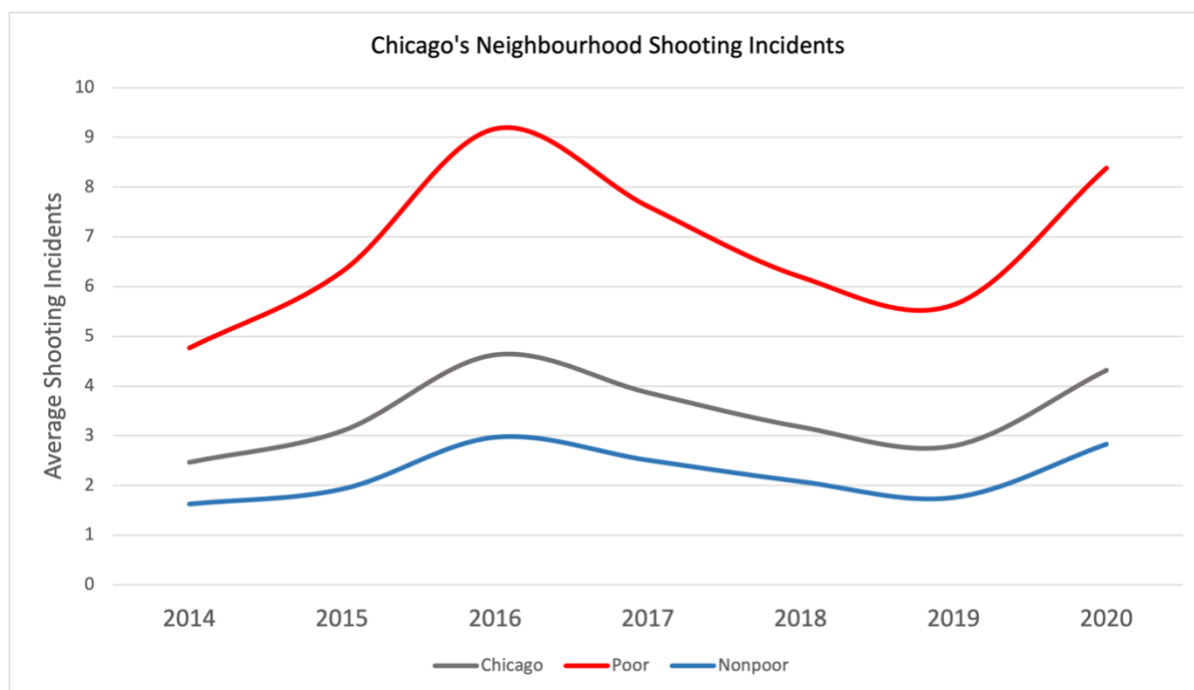


Figure 8 Annual Shooting Incidents in Chicago's Poor and Nonpoor Neighbourhoods

Similarly, in line with Sharkey and Marsteller (2022) that racial segregation is strongly associated with higher violence, Figure 9 shows that as the proportion of the black population increases in Chicago's neighbourhoods, shooting incidents also increase. This is clearly seen in all years that higher-black neighbourhoods experienced the highest shooting incidents compared to lower-black neighbourhoods.

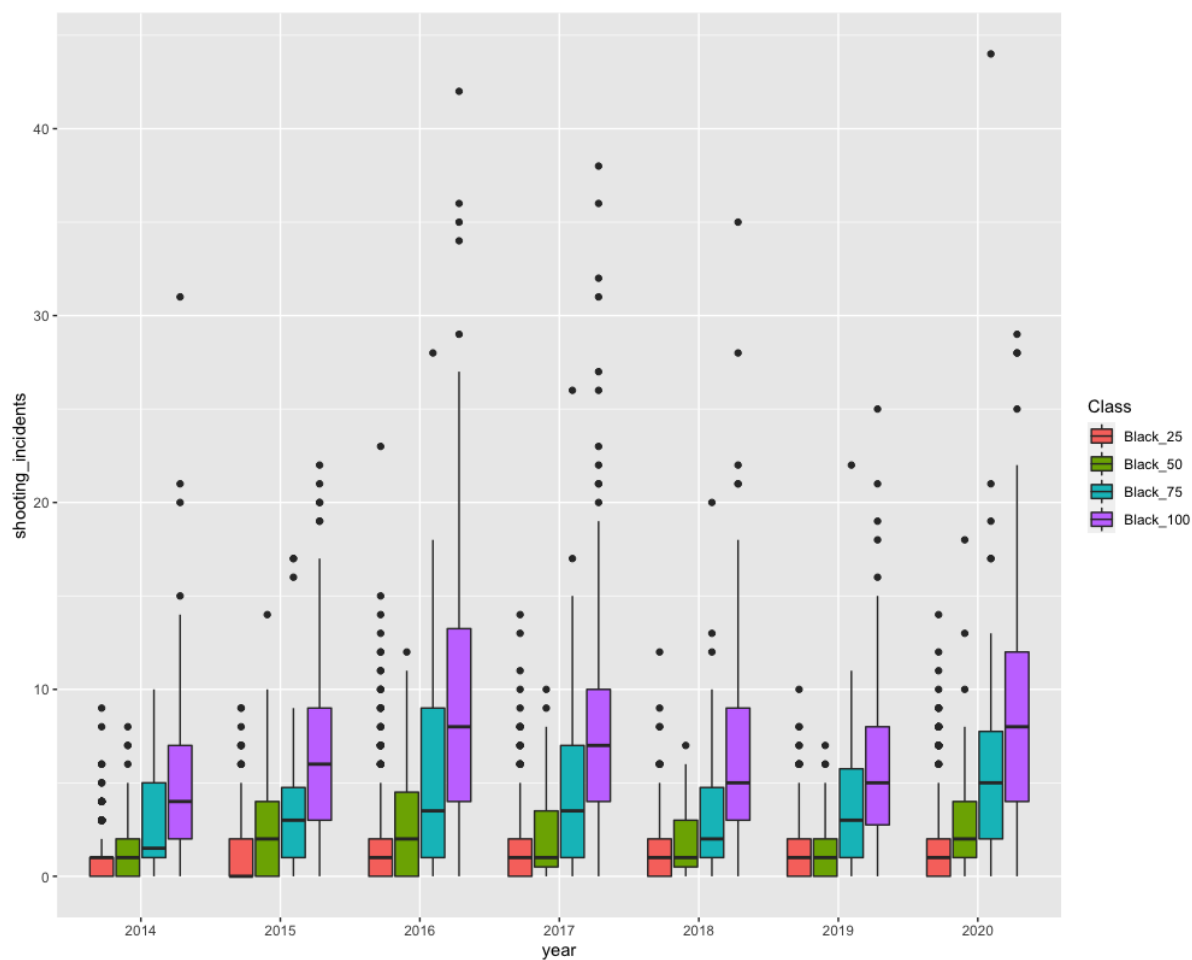


Figure 9 Average Shooting Incidents in Chicago's Neighbourhoods With Different Black Population Concentrations

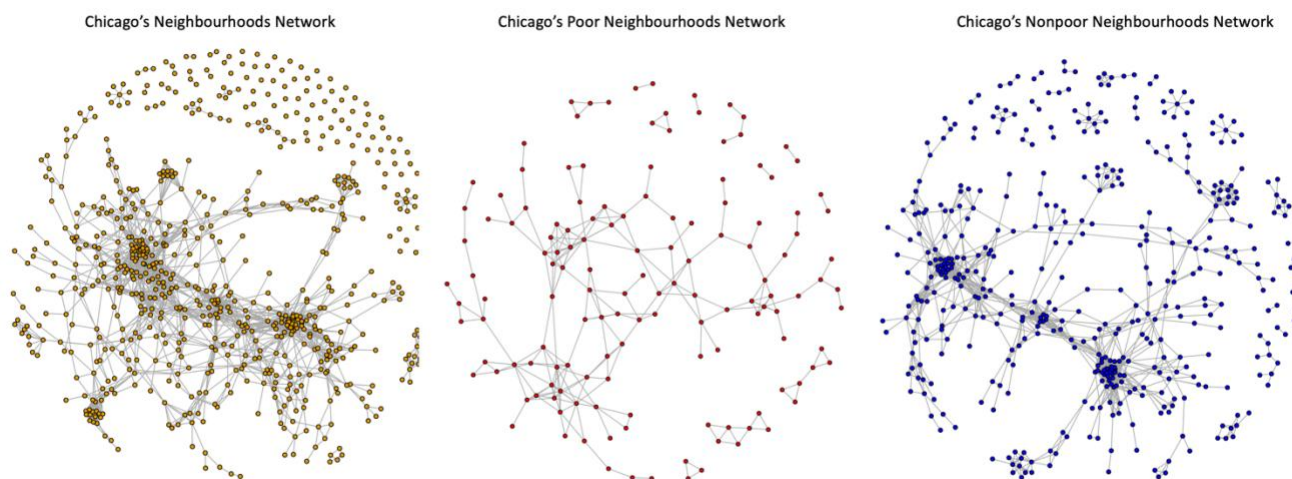


Figure 10 Crime Co-movement Network of Chicago's Poor and Nonpoor Neighbourhoods.

Figure 10 displays the shooting incidents' co-movement network of Chicago's neighbourhoods. Nodes represent the 731 neighbourhoods in the city, and the edges that link them represent the co-movement of shooting crime trajectories between neighbourhoods. That is, an edge exists between two nodes (neighbourhoods), which means that the shooting crime trajectories of these two neighbourhoods move in tandem during the study period of 2014 to 2020. The edge density of Chicago's network is 0.02, which indicates the proportion of edges in the network (5850 edges) over all possible edges that could exist. As can be seen in Table 1, the connectedness of the poor neighbourhood network is about 54% higher than both the nonpoor and the citywide network; indicates that the co-movement of shooting incidents is higher in poor neighbourhoods. A possible explanation is that the shooting incidents are retaliatory in nature and occur more among adversarial social networks that span multiple disadvantaged neighbourhoods (Morenoff et al., 2001, Tita and Ridgeway, 2007, Papachristos, 2009). It is encouraging to compare this finding with that found in a recent study by Sampson and Levy (2020) that provided suggestive evidence for the impact of such disadvantaged connectedness on the homicide and violence rates in Chicago.

Table 1 Chicago's Poor and Nonpoor Neighbourhood Networks Description

Network	Nodes	Edges	Network Connectedness (Density)
Chicago	731	5850	0.02
Nonpoor neighborhood	533	2893	0.02
Poor neighborhood	198	519	0.03

CHAPTER 3

When Crime Rates Move Together: What can we learn from linking neighbourhoods by their crime trajectories?

3.1 Introduction

A substantial body of research has documented the patterns of crime and their relationships to place. There has been a number of explorations of crime rates across various geographic units, including: states (Loftin and Hill, 1974); cities (Baumer et al., 1998); neighbourhoods (Bannister 2018, Byrne and Sampson, 1986; Schuerman and Kobrin, 1986, Raleigh and Galster, 2015); and micro units such as street segments (e.g., Weisburd et al., 1992; Groff and La Vigne, 2001; Weisburd et al., 2012). Recently, a growing body of literature has recognised the importance of understanding area-related crime trajectories over time. In mathematics, a trajectory is described as “the path which an object travelling through space and time follows” (Elragal and El-Gendy, 2012). When applied to the context of criminology, the crime trajectory is used to study the long-term patterns of crime within a geographic unit, in order to enhance the understanding of the development of crime over time (Weisburd et al., 2004; Weisburd et al., 2012). Moreover, understanding crime patterns and concentration plays an important role in the allocation of crime prevention resources (Sherman, 1995; Weisburd et al., 2004), and potentially increasing the efficacy of police intervention (Wheeler et al., 2016).

Weisburd et al., (2004) were the first to use trajectory analysis in the literature of crime and place. Their study aimed to determine whether sub-groups of geographic units (street blocks) evidenced similar patterns of crime trajectories over time as those of individual criminal careers. Following Weisburd et al. (2004), a considerable amount of literature has examined the crime

trajectory at micro places (e.g., street segments and intersections) revealing a considerable concentration of crime and stability over time (Curman et al., 2015; Anderson et al., 2016).

However, closer examination of the literature on trajectory analysis reveals several limitations. Firstly, relatively little attention has been paid to the development of crime at larger geographic scales such as neighbourhoods (Galster et al., 2007; Groff et al., 2010; Raleigh and Galster, 2015). Sampson et al. (2002) stated that “there is a clear need for rigorous longitudinal studies of neighbourhood temporal dynamics. ... We have scant information on how neighbourhood processes evolve over time” (Sampson et al., 2002, p.472). Bannister et al., (2017) noted: “research engaging with narrower geographies might fail to capture the ‘bigger picture’”. Secondly, previous studies have almost exclusively focused on the development of crime rates over time in relation to geographic units. What remains unclear, however, is whether certain characteristics of those geographic units tend to be associated with certain trajectories. Greater availability of data collected from small geographic units motivates a more in-depth investigation of firstly, how rates of neighbourhood crime evolve over time and secondly, the association between the influential factors and crime trajectories. Thirdly, previous research regarding such trajectories has primarily tended to include all crime times, so as to consider the development of the overall level of crime. Studying the overall crime trajectory has the potential to mask factors influencing specific crime types, while focusing on a specific type promises to provide further insights (Andresen et al., 2017; Bannister et al., 2017).

The research presented below seeks to address these limitations and has several contributions to the field of crime trajectories. First, this research proposes a 3-step approach to the analysis of property crime dynamics at neighbourhood level. This approach differs from prior research in its focus on crime trajectories within a macro geographic unit; namely,

neighbourhoods¹ and studying their characteristics. The neighbourhood level was chosen for this study because of the data availability of both crime rates and neighbourhood characteristics. The U.S. census data are not released at the level of micro places, such as street segments. Thus, given this research aims not only to examine the crime trajectory but also area characteristics, the use of micro places with the lack of data would be inappropriate for this research. Second, as discussed below, this study offers an alternative method to examine the trajectory of crime at neighbourhood level that has the potential to support both the field of crime trajectory analysis and any future research seeking to study the issue of the trajectory in relation to other fields. Third, this research examines the association between crime trajectory and neighbourhood characteristics by providing a deeper understanding of whether the same characteristics may behave differently in different groups of neighbourhoods and how this may affect the way crime modelling should be approached.

The aim of this chapter is to explore the crime trajectories at neighbourhood level and understand the impact of neighbourhood characteristics on the trajectory cluster membership. Using neighbourhood property crime rate for a 7-year period, this chapter is set out around the following three research questions:

1. Do neighbourhoods, in a given city, experience disparate crime trajectories?
2. Are there systematic drivers of group membership or is co-membership purely coincidental?
3. Are there structural differences in the determinants of crime levels across the different neighbourhood groups?

¹ The census tract will be used which is an area roughly equal to a neighbourhood, with a population ranged between 1200 and 8000, as established by the US Census Bureau for the purposes of analysis and used in the literature to represent neighbourhoods.

The remainder of this chapter is structured as follows. The chapter begins with an overview of the existing literature regarding crime and place, as well as crime trajectories, including relevant crime theories, and neighbourhood characteristics associated with crime distribution. This is followed by the theoretical framework. The subsequent sections describe the data, methods, and results. Finally, a conclusion provides a discussion of the main findings in addition to the implications and suggestions for future research.

3.2 Literature review

This section provides an overview of the existing literature regarding crime and place, crime trajectories, relevant crime theories, and neighbourhood characteristics associated with crime.

3.2.1 Crime and Place

A considerable amount of literature has been published on the criminology of place at different geographic units including street segments and intersections (Weisburd et al., 2012). Previous research examining geographical crime concentration has confirmed the existence of a clear spatial crime concentration at micro locations, with a high degree of stability over time. Sherman et al.'s (1989) examination of calls to police over all addresses and intersections in Minneapolis offers an early example of research regarding geographical crime concentration. The findings of their research showed that 3% of street addresses and intersections were responsible for 50% of requests for help from the police. Weisburd et al. (2004) examined 1.4 million crime reports in the city of Seattle, Washington, at a street block level between 1989 and 2002, employing group based trajectory modelling GBTM to establish whether street blocks evidenced crime patterns over time. The initial analysis revealed a 24% decrease in the overall rate of crime during

the study period. The results of the concentration analysis were in accord with those of Sherman et al. (1989), demonstrating a high geographical concentration of crime over time, with between approximately 4% and 5% of street blocks accounting for 50% of overall crime. It was notable that all crimes were located in between 45% and 53% of the street blocks, with no evidence of crime found between 47% and 52% of street segments. Furthermore, 1% of street segments experienced over 50% of the annual crime. In 2009, Weisburd et al. extended their previous study to examine juvenile arrest incidents in Seattle, Washington, for the same period at street block level. The results confirmed the concentration of incidents, revealing that between 3% and 5% of the street blocks accounted for all instances of arrest. Moreover, less than 1% of street blocks accounted for 50% of crimes.

In a seminal study in trajectory analysis, Weisburd et al. (2004) confirmed that micro places evidenced crime concentration and stability over time, thus emphasizing the significance of applying trajectory analysis and clustering techniques to geographic units. Being the first attempt to apply GBTM to geographic units, they examined the trajectories of 29,849 street segment crimes in the city of Seattle, Washington, between 1989 and 2002. The study grouped street segments into eighteen trajectories representing the trajectories of all street segments. Eight of the eighteen trajectories were classified as 'stable' (if a slope value for a trajectory was from -0.2 to $+0.2$) and these trajectories accounted for 84% of the street segments. Three of the eighteen trajectories were classified as 'increasing' (if a slope value for a trajectory was greater than $+0.2$) during the study period and accounted for approximately 2% per cent of street segments. The remaining trajectories were 'decreasing' (if a slope value for a trajectory was less than -0.2), and thus responsible for the overall lowering of crime levels in Seattle. While the results show that the city experienced a 24%

decrease in the rate of crime, this was not true of 86% of the street segments, i.e. this lowering of the overall rate of crime in the city due to only 14% of the street segments.

In order to test the generalizability of the Weisburd et al.'s (2004) study, Curman et al. (2015) were the first to attempt to replicate it. Also employing GBTM, they examined the crime trajectory of Vancouver, Canada, over a period of sixteen years (between 1991 and 2006). They identified general trajectories (stable and decreasing), with the majority of street segments categorized as stable. The crime rate in Vancouver decreased by 40% during the study period; however, similar to previous studies, this was found to be the responsibility of only a small fraction of street segments.

Although previous research has reported similar concentration for crimes, other research has examined the extent to which such concentration applies to different criminal related events. Weisburd et al. (2009) also examined the trajectories at street block level of juvenile arrests in Seattle between 1989 and 2002. The street blocks were categorized into eight groups, based on the nature of the juvenile offending. Although one group comprised 85% of the street blocks, only twelve arrests occurred in these street blocks. In contrast, one third of all juvenile arrest incidents occurred in three groups that included only 0.29% of the street blocks. Furthermore, Groff et al. (2010) studied patterns of crime incidents in Seattle using the same period and spatial units, in order to examine how identical crime trajectories (i.e. decreasing) were spatially distributed across the city, in particular whether street blocks with similar trajectories tended to be located in close proximity. The results revealed that the street blocks with high rates of crime were densely clustered, while those segments experiencing either no crime, or low levels of crime lacked any evidence of clustering, thus suggesting a uniform distribution.

A considerable number of studies have been published since Weisburd et al. (2004), using the GBTM technique to examine crime trajectories. Despite this method having proved effective in previous studies for identifying distinct trajectories, there are also several alternative techniques available to researchers, such as those used by Braga, Papachristos and Hureau (2010) and Andresen et al. (2017). Braga, Papachristos and Hureau (2010) used the growth curve method to investigate the trajectories of gun violence in micro places in Boston, Massachusetts between 1980 and 2008. The results demonstrated that, during the study period, gun violence in street segments generally followed two trajectories: a volatile trajectory or a stable trajectory. They found that the volatile group included 3% of the street segments and intersections responsible for more than 50% of violent crimes, including the use of guns. Similar to Weisburd et al. (2004), Braga, Papachristos and Hureau (2010) found that a small group of street segments and intersections were responsible for changes in trends of violence citywide over time. In a subsequent study, Braga, Hureau and Papachristos (2011) studied robberies in the same city over the same period, with similar results, i.e. a small group of micro locations were found to be the primary drivers of the overall changes in the number of robberies in the city during the study period.

In addition to the GBTM, in their study, Curman et al. (2015) used an alternative method to study crime trajectories in Vancouver, Canada. They used the k-means clustering method. They examined the trajectories of individual types of crime, as well as total crimes, for a period of sixteen years (i.e. between 1991 and 2006). The city of Vancouver experienced a drop in crime of approximately 41% during the study period. Although the K-means clustering affected the results by reducing the number of clusters, both methods led to similar results that only a small fraction of street segments contributed to the overall crime reduction.

The studies discussed above reveal that most research has previously focused on examining crime trajectories in terms of micro locations (i.e. street segments and intersections). While previous studies have confirmed a high crime concentration at such micro places, Bannister et al. (2017), Galster et al. (2007), Groff et al. (2010), and Raleigh and Galster (2015) highlighted the need to investigate larger spatial units like neighbourhoods. In a recent study, Bannister et al. (2017) examined the trajectories of the reduction of crime at neighbourhood level in Greater Glasgow between 1998/99 and 2012/13. They used Latent Class Growth Analysis (LCGA) to explore crime trajectories in 941 data zones in Glasgow. Data zones are output areas of 2011 Census which have populations of 500 to 1000 which are quarter of the size of census tracts used in the US that represent neighbourhoods. Their findings show that the city experienced a general reduction in crime during the period of study. Sixteen trajectories were identified, allocated to the following four categories based on changes in levels of crime: 'high' group, 'low' group, 'drop' group, and 'mixed group'. Overall, 95% of all neighbourhoods evidenced a reduction in crime. The high group included 1.6% of all neighbourhoods and contributed to the overall drop by 7.1%. The low group included 16.4% of all neighbourhoods and accounted for 4.2% of the reduction. The drop group included 25.3% of all neighbourhoods and was the highest contributor to the crime drop, i.e. 49.7%. Finally, the mixed group included the remaining neighbourhoods and accounted for 39% of the reduction in crime.

The studies discussed above revealed a notable concentration and stability of crime trajectory at different geographic units (i.e., street segments and neighbourhoods). The following section establishes why there is such variation in crime rates across neighbourhoods and whether certain characteristics of those geographic units tend to be associated with crime.

3.2.2 Neighbourhood Characteristics and Crime

Historically, a considerable degree of research has examined the reasons for rates of crime being higher in some neighbourhoods than others. Miethe and Meier (1994) divided the theoretical frameworks studying the relevant factors into three categories: (1) the perspective of the offender; (2) the perspective of the victim; and (3) the perspective of the context. These are discussed in turn.

The perspective of the offender focuses on an individual's motivation to commit crime. Several theories have been developed to understand the mechanisms influencing the decision-making of offenders. For example, rational choice theory posits that the decision is a rational choice, based on an evaluation of costs and benefits (Cornish and Clarke, 1987; Felson and Boba, 2010). Although this decision-making process is constrained (being limited by the availability of relevant information and knowledge, time and resources), it is considered rational as the offender generally makes a calculation based on risk and reward (Paternoster and Bachman, 2001). Blokland and Nieuwebeerta (2005) argued that an offender selects a suitable target based on multiple criteria: (1) a neighbourhood (or property) requiring less effort to enter; (2) places that appear to contain valuable items; and (3) the impression of being unlikely to be apprehended. This thus considers that an offender will commit a crime if the probability of benefit (i.e. target attractiveness and accessibility) is higher than the probability of cost (i.e. the likelihood of being caught) and vice versa.

In contrast to the previous perspective, the perspective of the victim focuses on the makeup of a suitable target and increases the chances of being the victim of crime. For example, routine activity theory assumes that "a crime is expected to occur when suitable victims, motivated

offenders and the absence of capable guardians converge in space and time” (Cohen and Felson, 1979, p. 589)

While the first two perspectives emphasise people, the perspective of context considers the important role played by neighbourhood characteristics and social processes (i.e. social disorganization, social control and collective efficacy) in levels of crime within neighbourhoods. Considerable previous research has recognized the importance of social disorganization in understanding crime taking place in neighbourhoods and communities.

Thus, social disorganization theory, developed by Shaw and McKay (1942), assumes that informal social control has previously proved an effective inhibitor of neighbourhood crimes. Sampson, Raudenbush and Earls (1997) extended social disorganization theory to formulate collective efficacy theory, which is defined as the ability of neighbourhood and community residents to recognize their common values and maintain social control, thus promoting collective efficacy and enabling them to act as capable guardians. Such mechanisms have been documented in studies of crime and appear strongly correlated with: (1) community social cohesion (Bellair and Browning, 2010); (2) residential stability (Sampson and Groves, 1989; Hipp, 2007); and (3) rates of home ownership (Dietz and Haurin, 2003). By contrast, weak collective efficacy was found in neighbourhoods possessing: (1) high levels of racial heterogeneity; (2) low economic status; (3) family disruption; and (4) high residential mobility (Sampson and Groves, 1989; Harcourt and Ludwig, 2006).

A growing body of criminological literature has investigated both social disorganization theory and opportunity theory and their related variables. Furthermore, a large volume of published studies has outlined the impact of neighbourhood characteristics on crime rates. Despite the availability of data collected from various spatial units, most studies in the field of crime trajectory

have focused solely on trajectory development and crime concentration. To date, few studies have attempted to investigate the association between crime trajectories and area related characteristics, with two notable exceptions (e.g., Weisburd et al., 2012; Bannister et al., 2017). In their comprehensive work, Weisburd et al. (2012) studied crime trajectories at the level of street blocks and extended their investigating to examine the impact of social disorganization and opportunity theories related variables on crime trajectory group membership. They used multinomial logistic regression to examine various neighbourhood characteristics, in order to establish what increases the probability of certain street segments to be in a specific trajectory group. Commencing with opportunity variables, they found that the presence of motivated offenders (i.e. high-risk juveniles) increased the likelihood of a street being placed in a high chronic-crime trajectory. Each additional employee (i.e. suitable target) in a street was associated with an 8% increase in the likelihood of a street being in a chronic- crime group. In addition, opportunity theory assumes that the probability of crime is increased by a convergence of motivated offenders and suitable targets. Consequently, the results showed that every additional bus stop in a street doubled the likelihood of it being in chronic-crime trajectory. The results also showed that high schools and other public facilities increased the probability of a street experiencing chronic-crime trajectory by 25%. Finally, a significant predictor consisted of the percentage of vacant land, with every 1% increase associated with a 50% increase in the likelihood of a street being in a high chronic- crime group.

Likewise, social disorganization variables demonstrated an association with the probability of a high crime trajectory. For example, every unit increase in the value of residential property decreased the likelihood of a chronic-crime trajectory by 30%. On the other hand, the presence of social housing increased the probability of being in a high crime trajectory by 10%. The presence of active voters was included in the model as an indicator of collective efficacy, with the results

demonstrating that streets having no active voters (i.e. relative to all registered active voters) were associated with a 96% decrease in being categorised as having a chronic-crime trajectory.

Bannister et al (2017) studied the association between the relative change of neighbourhood characteristics and crime drop trajectories at a neighbourhood level in Greater Glasgow between 1998/99 and 2012/13. They examined a number of deprivation variables (e.g. median household income and unemployment rate), in addition to other variables (e.g. rate of home ownership, age structure and business addresses). Their findings revealed that changes in the characteristics of some neighbourhoods were associated with a reduction in the level of crime trajectories. For example, the highest increase in household median income was found in neighbourhoods experiencing a decrease in rates of crime (i.e. the ‘drop’ and ‘low’ groups). Furthermore, the results revealed that the smallest rise in private rented accommodation was found in the ‘drop’ and ‘low’ groups. In addition, the presence of crime attractors² (i.e. business premises) was found to have an impact on crime rates. Thus, the ‘high’ group included the greatest number of business premises, while the ‘drop’ and ‘low’ groups had the greatest reduction in business establishments.

3.3 Theoretical framework

Two important themes have emerged from the studies discussed so far. Firstly, crime and place research has confirmed considerable geographical concentrations of crime and stability over time. Secondly, certain neighbourhood characteristics appear to be associated with higher crime rates, although the evidence available to explain this relationship is inconclusive. Scholarship on the area’s characteristics and their association with crime rates typically relay in a set of crime and

² Commercial areas such as business premises found to be associated with crime as being public places that attract suitable targets (people who have money or goods) for offenders.

place theories such as social disorganization theory and opportunity theories (i.e., Rational choice theory, routine activity theory, and crime pattern theory).

Social disorganization: Developed by Shaw and McKay (1942), assumes that informal social control has previously proved an effective inhibitor of neighbourhood crimes. Sampson, Raudenbush and Earls (1997) extended the social disorganization theory to formulate collective efficacy theory, which is defined as the ability of neighbourhood and community residents to recognize their common values and maintain social control, thus promoting collective efficacy and enabling them to act as capable guardians. Such mechanisms have been documented in studies of crime and appear strongly correlated with: (1) community social cohesion (Bellair and Browning, 2010); (2) residential stability (Sampson and Groves, 1989; Hipp, 2007); and (3) rates of home ownership (Dietz and Haurin, 2003). By contrast, weak collective efficacy was found in neighbourhoods possessing: (1) high levels of heterogeneity; (2) low economic status; (3) family disruption; and (4) high residential mobility (Sampson and Groves, 1989; Harcourt and Ludwig, 2006).

Rational choice: The theory posits that the crime decision is a rational choice, based on an evaluation of costs and benefits (Cornish and Clarke, 1987; Felson and Boba, 2010). Although this decision-making process is constrained (being limited by the availability of relevant information and knowledge, time and resources), it is considered rational as the offender generally makes a calculation based on risk and reward (Paternoster and Bachman, 2001). Blokland and Nieuwebeerta (2005) argued that an offender selects a suitable target based on multiple criteria: (1) a neighbourhood (or property) requiring less effort to enter; (2) places that appear to contain valuable items; and (3) the impression of being unlikely to be apprehended. This thus considers that an offender will commit a crime if the probability of benefit (i.e. target attractiveness and

accessibility) is higher than the probability of cost (i.e. the likelihood of being caught) and vice versa.

Routine activity: This theory assumes that “a crime is expected to occur when suitable victims, motivated offenders and the absence of capable guardians converge in space and time” (Cohen and Felson, 1979, p. 589).

Crime pattern: The theory seeks to integrate people-based and context-based approaches into a single overarching framework (Brantingham and Brantingham, 1984). It explores the interactions of offenders, victims, and opportunities across time and space. The crime-pattern theory also explains the key role that places and their characteristics play in influencing the likelihood of a crime and how places become crime hot spots.

These theories provide useful framework and insights into the attributes of geographic areas and population that typically have association with crime rates. However, in terms of offering a comprehensive portrait of the similarity in crime trajectories, existing crime trajectory literature is limited. Earlier empirical studies of place and crime have typically focused on confirming the concentration of crime in micro areas and studied the association between crime and neighbourhood characteristics in cross-sectional research. Hence, the specificities of potential factors linking similar neighbourhoods’ trajectories clusters remain unclear. Thus, important lines of enquiry raised include: what factors lead neighbourhoods to be in the same crime trajectory cluster; whether the neighbourhood characteristics established in the prior cross-sectional research have similar effects on neighbourhood crime trajectories; and whether the membership of crime trajectory clusters is driven by different characteristics.

Two possible complementary explanations are proposed here. The first is that similarities in the sociodemographic, resources and physical attributes of the neighbourhoods make them more

likely to respond in similar ways to external changes because there are similar causal mechanisms at work that determine crime in both areas. For example, if crime in neighbourhoods A and B is primarily caused by poverty, the national cuts in welfare spending may affect crime rates in both neighbourhoods in a similar way.

The second explanation is that there are networks of information that link the neighbourhoods through which, innovation about crime, crime opportunities, conflict between rival gangs, trends in violence, etc. are transferred through information cascades (Pryce et al., 2018). These networks may be formed through crime families and gangs that have a presence in multiple neighbourhoods. There may be networks of connections between different crime gangs formed through alliances, common friendships, time in prison together, etc. They also are linked through school friendships, commuting flows, trade links in crime. Such networks are more likely to emerge between similar neighbourhoods because “social networks tend to be homophilous” (McPherson et al., 2001, p. 416). Both these theories, if true, would suggest systematic drivers of the co-movement of crime. Empirically, this would mean that group membership of similar clusters of crime trajectory will have systematic drivers in terms of similarities of the neighbourhood characteristics.

3.4 Study location

This study utilises data on Cleveland, the second largest city in the state of Ohio. It is located in north eastern Ohio, at the mouth of the Cuyahoga River. The study location was chosen for the following reason. Cleveland, OH is an American standard city that has a population of 383,793. However, in 2017, the crime rate for the city was 786 crime per 100,000 people, which is 2.8 times greater than the national average and higher than 98% of US cities (City-data.com, 2017). Hence, the fact of it being a high-crime city as well as the availability of crime data motivate a more in-

depth investigation of how Cleveland crime rates move over time. According to the Census Bureau QuickFacts (2017), the racial composition of Cleveland was as follows: around 50% of Cleveland residents are Black or African Americans, 40% are White, with the remainder of mixed or other racial heritage.

3.5 Crime data

The property crime data employed in this current research were obtained from the Northeast Ohio Community and Neighbourhood Data for Organizing (NEOCANDO), an innovative data tool developed by the centre of Urban Poverty and Community Development at Case Western Reserve University. The data were obtained at census tract level for years 2010-2017 and consist of the rate of property crimes (i.e. burglary, vehicle theft, arson, and larceny) per 1000 for each census tract. A census tract is an area roughly equal to a neighbourhood established by the Census Bureau for the purposes of analysis, with a population ranged between 1200 and 8000 and have been used in the literature to represent neighbourhoods. There were 175 census tracts in the city of Cleveland (169 included in the analysis following the exclusion of outliers).

3.6 Neighbourhood characteristics

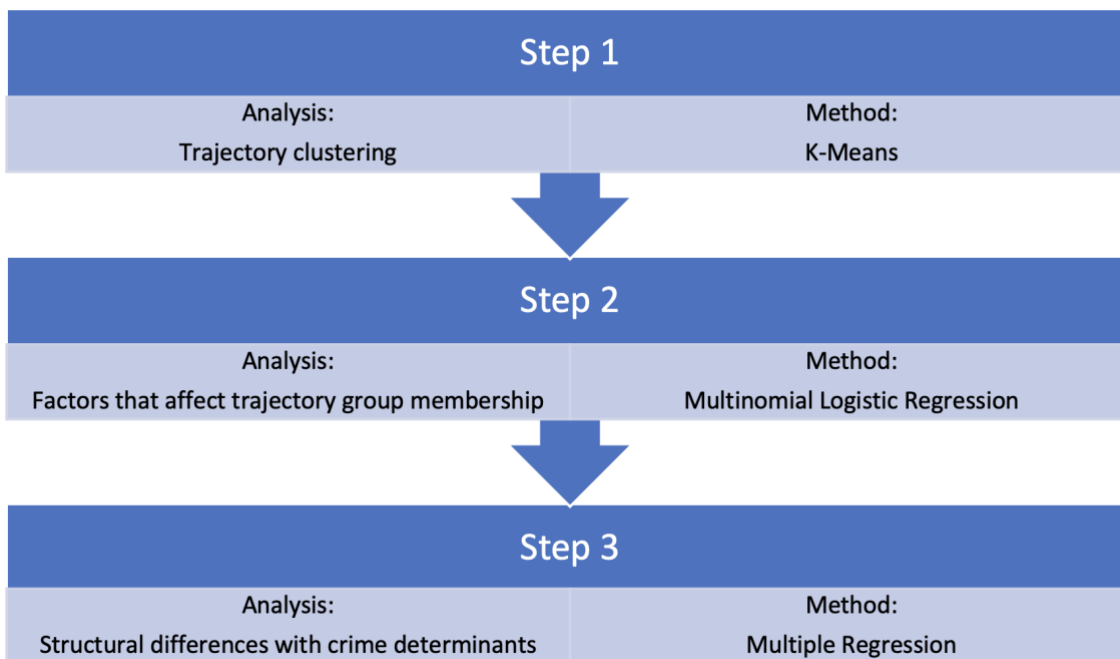
Opportunity theories, social disorganization theory – and its later revision and development in the collective efficacy theory by Sampson et al. (1997) - have played a crucial role in understanding the crime problem in the crime and place criminology (Weisburd, 2012). While the opportunity theories focus on the situational properties of locality, the social disorganization theories excel in the specification of the neighbourhood and population characteristics that have a potential association with the crime problem (Bannister 2018). Given the established impact of the opportunity and collective efficacy theories related variables on the crime and place literature,

a selected number of such variables were selected based on the availability of the data. Being relied on the open data, I could not measure all the related variables, and this is an important limitation of this thesis, as discussed more in the conclusion.

In order to study low economic status, the poverty level was examined through the proportion of households using food stamps, and the proportion of households below the poverty limit in a neighbourhood (Sampson and Groves, 1989 and Hipp, 2007). Single parent family was measured as the proportion of single parent family with children and this variable have been used in previous research as a possible indicator of the lack in supervision of youth and guardianship (Raleigh and Galster, 2015). To study the impact of the racial heterogeneity, the percent of minorities in a neighbourhood was measured (Blau and Blau, 1982; Messner, 1983; Bursik, 1986). To examine the residential stability and instability, the percentage of owner occupants and the percentage of residents living in the neighbourhood for five or more years was measured, as well as the percentage of renters (Sampson and Groves, 1989; Hipp, 2007). Age structure was understood through consideration to the proportion of young people (i.e. those aged between fifteen and twenty-four) and older people (i.e. aged fifty-five and older) (Bannister 2018). Finally, in order to study the impact of crime ‘attractors’, the proportion of business addresses among the total postal addresses in a neighbourhood was calculated (Brantingham and Brantingham 2008; Bannister et al., 2017).

3.7 Methods

Figure 11 Analysis steps



I propose a 3-step approach to analysing the co-movement of crime between neighbourhoods:

Step (1): Cluster Neighbourhoods by their Crime Trajectories

In order to examine similar neighbourhood trajectories over time, this study required a method to model neighbourhood property crimes and estimate the rate of change for crime trajectories. The annual property crime rate and the K-means algorithm were therefore employed to identify clusters of neighbourhoods experiencing similar crime trajectories over time. K-means is a non-parametric clustering method originally developed by Calinski and Harabasz (1974) that aims to identify clusters of observations that share similar traits. The K-means statistical technique has been used in the criminology literature since Huizinga et al. (1991) that used K-means algorithm to cluster the offending trends of youth over two years (1987-1988). Another implementation of K-means in the crime literature was by Mowder et al. (2010) who used K-means

algorithm to study the resilience of male and female offenders in a juvenile facility. In a more recent article, Curman et al (2015) used K-means method to explore and cluster the crime trajectories of the street segments in the city of Vancouver over a 16-year period (1991-2006).

Step (2): Analyse the Drivers of Group Membership

The second step in our 3-step approach aims to examine the systematic factors that determine group membership. In particular, whether certain neighbourhood features affect the probability of being in a certain neighbourhood group. Accordingly, a multivariate statistical method is needed in order to understand these relationships. The independent variables examined in this method are neighbourhood characteristics. The phenomena that we want to understand is the dependent variable, which is the neighbourhood trajectory groups. The use of the neighbourhood trajectory group as a dependent variable (i.e. multi categorical variable) creates an additional statistical complexity for this analysis (Weisburd et al., 2012). Therefore, multinomial logistic regression is used here for two reasons. Firstly, this technique provides a solution to this complexity by examining all different comparisons simultaneously (Weisburd and Britt, 2012). Secondly, it provides a set of coefficients that help to explain the effects of the independent variables on group membership.

Three models were developed to examine the influence of characteristics on group membership. The first model included and examined the effect of the change over time in neighbourhood characteristics being in a certain trajectory group. The second model included both the relative change and baseline estimates in order to examine whether the initial estimates of characteristics of a neighbourhood influence its probability of being in a trajectory group. The third model (presented in the results section below) included all previous variables (the change and the initial estimates of neighbourhood characteristics) in addition to the initial estimate of property

crime rate (first year crime rate). This measure assesses whether the initial crime rate affects the likelihood of a neighbourhood being in a certain trajectory group. This modelling strategy was the same approach as that used by Weisburd et al. (2012).

Step (3) Testing for Structural Differences Across Neighbourhood Groups in the Determination of Crime

Finally, if there are systematic factors that drive group membership, this raises the question of whether these factors cause structural differences with the determination of crime levels across the neighbourhood groups. Therefore, in order to examine whether the same variables would behave differently in different groups, multiple regression models were developed. Then, interaction effects were incorporated into the models. Significant interaction occurs when the influence of one predictor variable (e.g. poverty rate) on the outcome variable (i.e. property crime rate) changes as values of another explanatory variable changes (i.e., cluster). This assumes that it is possible that the impact of poverty on crime rate differs depending on the trajectory cluster a neighbourhood belong to. In this situation, it might be misleading to assume that all neighbourhoods share the same slopes between poverty and crime rate. This will make their respective slopes to vary to represent their differing relationships between poverty and crime rate.

3.8 Results

Step (1) Results of crime trajectory clustering

Estimating a crime trajectory for each neighbourhood demonstrates the variety of distinctive trajectories. Figure 12 shows the crime trajectory for each neighbourhood ($n = 169$) between 2010 and 2017. As shown in Figure 12, there can still be a number of difficulties in identifying the main trajectories, due to the variety in shapes of all neighbourhoods. It is therefore vital to cluster these crime trajectories, in order to identify the representative trajectories.

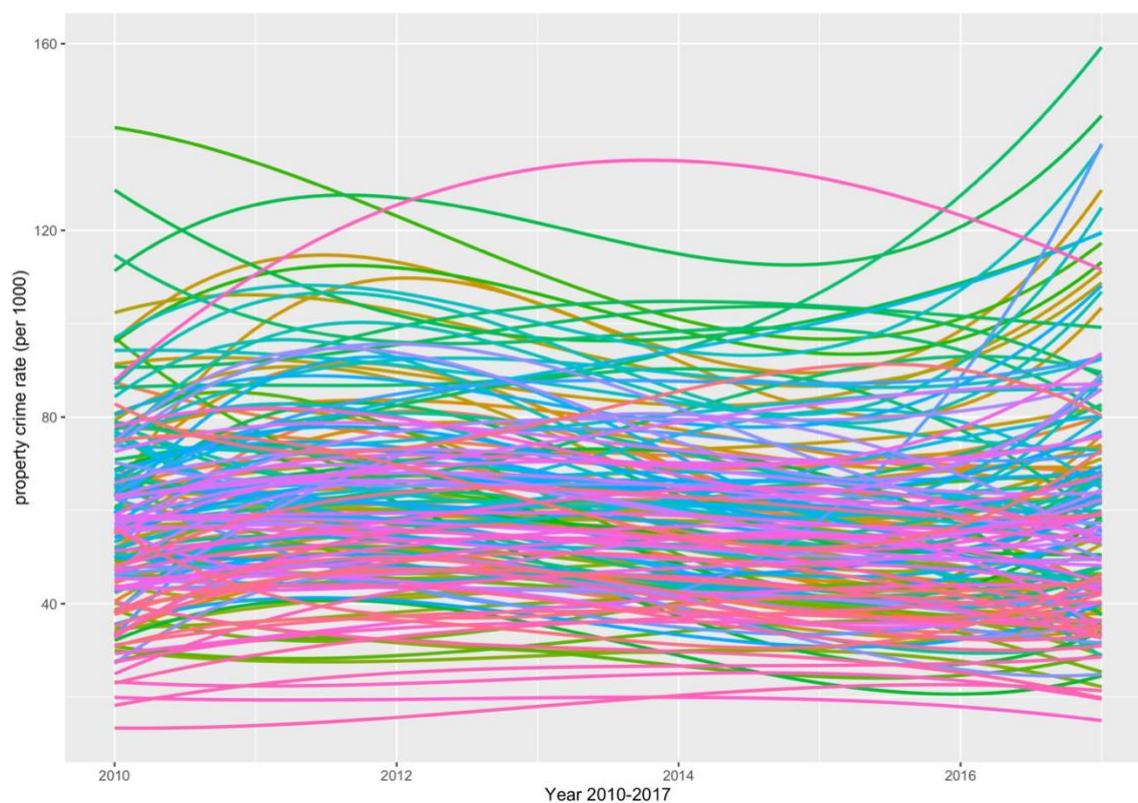


Figure 12 The crime trajectory for each neighbourhood (n = 169) between 2010 and 2017

Hence, following the estimation of the rate of change using simple regression, the estimated coefficients were used to cluster these trajectories using k-means algorithm. The k-means clustering algorithm (Forgy, 1965; MacQueen, 1967; Hartigan and Wong, 1979) has been one of the most popular tools for clustering data. One of the challenging problems in clustering analysis is choosing an optimal number of clusters before fitting. There are several methods can be used to find the optimal number of clusters, such as the elbow method, which was chosen in this study. The elbow method is one of the most popular methods used for determining the optimal number of clusters in a data set (Andrew, 2012). The elbow plot visualizes the total within-cluster sum-of-squares against K (i.e. the number of clusters). The idea is that the sum of square value starts very high when $k = 1$ and then decreases as the number of clusters increases. At some point, the value

will drop dramatically at a specific k value. After that, it reaches a plateau and then decreases very slowly when we increase it further. This is the point we look for, which indicates the optimal number of clusters (Kodinariya and Makwana, 2013; Bholowalia and Kumar, 2014). Therefore, three clusters were selected based on the elbow method.

Three trajectories were identified by using the k-means clustering method, representing the distinctive trajectories in all neighbourhoods over the period of study (see Figure 13). The neighbourhoods were divided into three main crime trajectory groups: Group 1: the increasing group; Group 2: the decreasing group; and Group 3: the stable group.

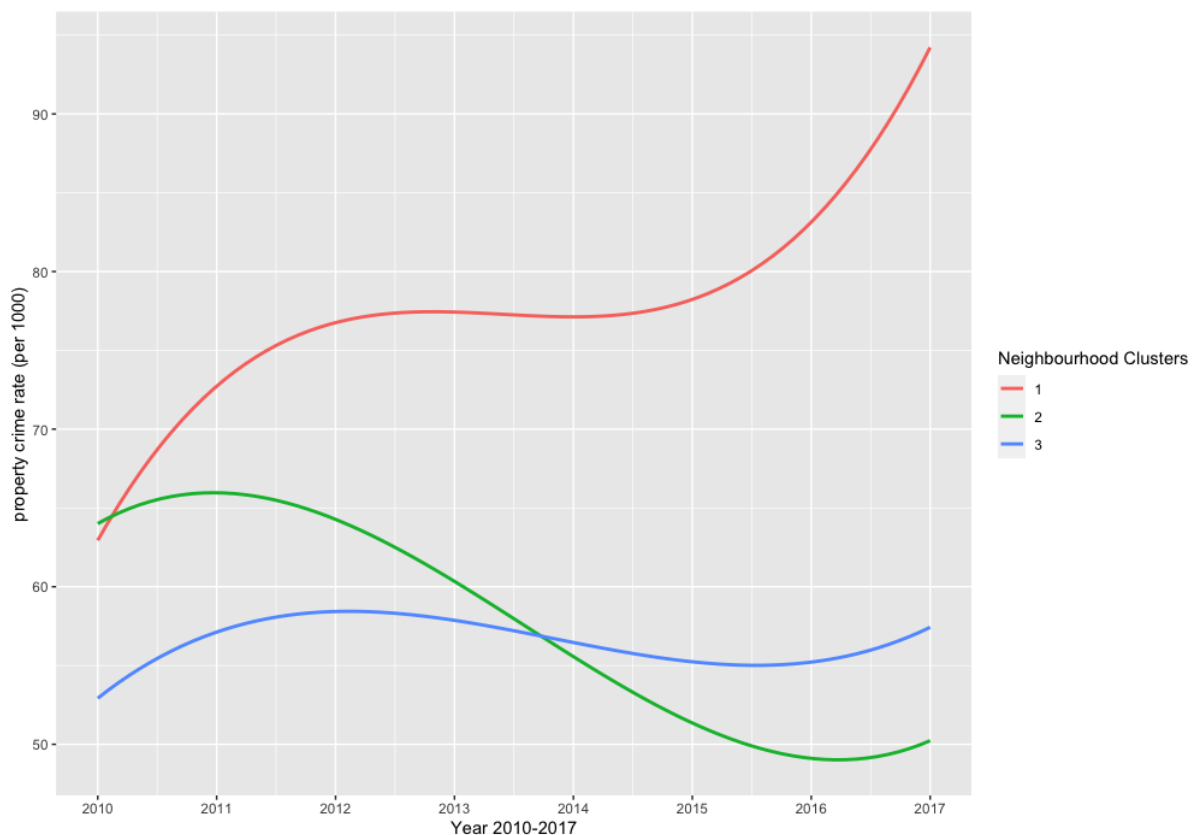


Figure 13 Results from clustering the crime trajectories representing the distinctive trajectories

Group 1 contained the neighbourhoods experiencing an increase in property crime rate (per 1000) over the study period, with a relative mean increase of 48% (i.e. twenty two times higher than the citywide relative change). Group 2 contained the neighbourhoods showing a relative decrease in excess of 22% in property crime over the study period (i.e. ten times lower than the relative change of the study area). Group 3 contained the neighbourhoods experiencing no major relative change in property crime over the study period.

Over the study period, the neighbourhoods' property crime rate per 1000 in Cleveland increased by 2.2%. However, not all neighbourhoods experienced the same crime trajectory. Group 1 comprised 15.3% of all neighbourhoods experienced a 48.5% increase over the study period; Group 2 comprised 35.5% of all neighbourhoods demonstrated a 22.3% decrease in property crime rate over the study period; and Group 3 comprised 49.1% of all neighbourhoods revealed a number of relative changes in the level of crime, with no distinctive changes identified over the study period. Table 2 presents the comparisons of crime rates between the three groups in the first and last years of the study period.

Table 2 Neighbourhood groups and their crime rate change over time

Group	Group membership rates		Mean crime rate (per 1,000)		Change in mean crime
	Number	%	2010	2017	2010 - 2017
Total	169	100	57.8	59.1	+ 2.23
Group 1	26	15.3	62.22	92.40	+ 48.51
Group 2	60	35.5	63.44	49.26	- 22.34
Group 3	83	49.1	52.37	55.74	+ 6.42

Step (2) Results of group membership analysis

Table 3 presents the results of the multinomial logistic regression models used to examine the influence of neighbourhood characteristics on trajectory group membership. One complication of using multinomial regression is that the results show the parameter estimates for each trajectory group relative to an excluded group called the reference category. In this analysis, each trajectory group was examined in relative to the other two groups which produced a large number of parameter estimates. Thus, the comparison between group 1 and group 2 relative to group 3 is discussed here because it showed a clearer effect of the independent variables on group membership as the same variables in the other group comparisons seem to have a very small effect. Table 2 shows the results of the analysis comparing group 1 and group 2 relative to group 3. Due to the nonlinearity of the coefficients in such method, it might be difficult to interpret the parameter estimates (Weisburd et al., 2012). Thus, the focus will be on the change in the odds ratio. The odds ratio indicates to the proportional change in the likelihood of being in one group as opposed to the reference group. For example, if the odds ratio is 1.15, that would indicate that a one unit increase in the independent variable increases the odds of being in one group (compared to the reference group) by 15%.

From the model estimates presented in Table 2, two variables showed an influence that decreases the likelihood of being in group 1 compared to group 3, poverty and unemployment. That is, every 1 percent increase in poverty and the unemployment rate decreases the likelihood of a neighbourhood being in group 1 by 3% and 8% respectively. However, different factors found to reduce the likelihood of being in group 2 compared to group 3. That is, every 1% increase in both the proportion of residential instability and family disruption, reduces the probability of a neighbourhood being in group 2 by 3%.

On the other hand, two characteristics were found to increase the probability of being in the group 1 compared to group 3. First, the proportion of business addresses in a neighbourhood shows the biggest effect. That is, every 1% increase in business premises, increases the likelihood of a neighbourhood being in group 1 by 18%. Second, the young population increases the probability of being in group 1 by 12%. On the other hand, same characteristics did not show an effect in group 2.

In summary, the purpose of this analysis was to examine how neighbourhood characteristics affect the membership of a neighbourhood being in a certain group. Interestingly, the results of this analysis showed that the membership of neighbourhood groups was influenced by different characteristics. In other word, some variables were found to have an influence on one group membership, but the same variables did not show an impact on the other group membership.

Table 3 Multinomial Logistic Regression Results of Impact of neighbourhood characteristics (including change in variables) on likelihood of being in Group1 & Group3 vs. Group2.

Variable	Group 1 to Group 3	Group 2 to Group 3
	Odds ratio	Odds ratio
Ethnic heterogeneity	1.07	1.00
Ethnic heterogeneity (change)	1.00	0.99
Poverty	0.97	0.99
Poverty (change)	1.00	1.00
Family disruption	1.00	0.97
Family disruption (Change)	1.00	1.00
Business premises	1.18	1.00
Business premises (change)	1.03	1.00
Residential instability	1.00	0.97
Residential instability (change)	1.00	1.00
Unemployment	0.92	0.97
Unemployment (change)	0.99	0.98
young people 15-24	1.12	1.01
Young (change)	1.00	0.99
Crime rate 2010	0.95	0.98

Step (3) Results of tests for structural difference in crime determination across neighbourhood clusters

In order to examine whether the same variables behave differently in different groups of neighbourhoods, a regression model with interaction terms for each group was developed. Table 3 describes models 1 and 2, which include selected variables according to their potential, as demonstrated in previous research to impact the crime rate at neighbourhood level. The purpose of this analysis is to identify whether there are structural differences across the three groups of neighbourhoods that inform the relationship between crime levels and our list of explanatory variables. As presented in the previous results, the trajectory analysis shows that the neighbourhoods in the Cleveland city experienced various crime trajectories over the study period. The unobserved differences in causal pathways are likely to mean that same explanatory variables might have different effect on the crime levels across the three clusters of areas. To verify this, we examined whether the effect of the explanatory variables in Table 3 are stable across the three clusters of areas. In other words, whether there are significant differences in predictors coefficients across clusters.

Table 4 regression and interaction test results of the neighbourhood characteristics for Group 2, Group 3 comparing to Group 1.

Variable	(Model 1) Base Model β (SE)	(Model 2) Interactions β (SE)
Intercept	9.60** (3.64)	4.55 (4.11)
Poverty	0.31** (0.11)	0.70*** (0.19)
Unemployment	0.19 (0.15)	
Family disruption	0.26*** (0.05)	0.21* (0.08)
Ethnic heterogeneity	0.27 (0.22)	
Residential Instability	- 0.06 (0.10)	
Young population 15-24	0.32 (0.20)	
Business premises	2.17*** (0.23)	2.67*** (0.34)
Interaction Test		
Group 2 (Decreasing)		77.04*** (13.30)
Family Disruption: Group2		-0.44* (0.18)
Poverty: Group2		-0.68* (0.28)
Business premises: Group2		-1.67*** (0.47)
Group 3 (Stable)		10.76 (6.15)
Family Disruption: Group3		0.07 (0.10)
Poverty: Group3		-0.42* (0.21)
Business premises: Group3		-0.57 (0.54)
<i>Note:</i> *p<0.05 **p<0.01 ***p<0.001		

Table 4 presents the results for the two models. Model 1 includes all variables and Model 2 include the significant variables with interaction terms. The first model examines the impact of explanatory variables on the crime rate for all neighbourhoods. As shown in Table 4, controlling for all predictor variables, poverty has a significant effect on crime rate ($\beta = 0.31$). On average, and controlling for all predictor variables, each extra one percent in poverty raises the crime rate by 0.31 percent. Family disruption is also significantly and positively ($\beta = 0.26$) related to crime rate, holding constant effect of other predictor variables. On average, and controlling for the other variables, the increase in the proportion of disruption family in a neighbourhood raises the crime rate by 0.26 percent. And business premises also has a significant effect, and the coefficient is positive ($\beta = 2.17$). This shows that every one percent increase in the business premises raises the crime rate by 2.17 percent.

The purpose of this analysis is to examine whether crime determinants show a significant differences in terms of their impact across neighbourhood groups. Therefore, an interaction test was deployed to verify whether neighbourhood characteristics effect differ across groups. The interaction analysis examines whether there are significant differences in terms of explanatory variables effect on the dependent variable (Crime rate) in different groups (group 2 and group 3) comparing to a reference group (Group 1). Table 3 shows that the interaction terms are significant in all significant variables (poverty, family disruption and business premises) when comparing group 2 to the reference group (i.e. group 1) and significant in one variable (poverty) in the comparison of group 3 to group 1. In effect, the interaction term shows the difference in effect of an additional percent in predictor variables between clusters. For example, while higher poverty in a neighbourhood was associated with higher crime rate, the effect for group 2 is 0.68 percent and for group 3 is 0.42 percent lower compared to group 1. Similarly, the effect of family

disruption in group 2 is 0.44 lower compared to its effect in group 1. Also, the effect of business addresses for group 2 is 1.67 percent lower. On the other hand, the effect of family disruption and business addresses for group 3 do not have significant differences.

In summary, model 1 shows that three of the neighbourhood characteristics (poverty, family disruption and business addresses) significantly and positively associated with crime rate. However, significant differences of their effect seen in the interaction model results. Thus, the interaction test results confirmed that same variable may operate differently in different groups. For example, as shown in Table 4, a significant difference in all significant variables was found between group 2 and group 1. Also, a significant difference was found in the poverty rate between group 3 and group 1. In other words, the results show that poverty, family disruption and business addresses affect crime rate but they affect crime rate in group 1 by substantially more than affect crime rates in group 2.

3.9 Conclusion

The consensus of the crime trajectory literature is that spatial units (e.g., street segments and neighbourhoods) show notable crime concentrations and stability across time. However, scholarship on crime trajectories typically overlooks the underlying factors that link similar areas and the influence of attributes of areas on their crime trajectories. Understanding the crime trajectory for a set of neighbourhoods and then identifying similar trajectories are indispensable and essential aspects of an exploration of neighbourhood crime over time. Understanding the impact of neighbourhood characteristics on cluster membership then offers explanation as to whether there are systematic drivers of group membership, and whether such factors in group membership have an implication for how to model crime; in other words, whether independent variables behave differently in different groups of neighbourhoods.

The property crime data for the city of Cleveland, Ohio, between 2010 and 2017 was analysed. In addressing the first aim of this study to identify the distinct groups of crime trajectories, three groups of neighbourhoods were identified based on their similarity in rate of change of the crime trajectory over the study period. Group 1 (increasing) contained the neighbourhoods experiencing an increase in property crime, with a relative mean increase of 48%. Group 2 (decreasing) comprised the neighbourhoods that experienced a relative decrease in excess of 22% in property crime. Group 3 (stable) included the neighbourhoods experiencing no major relative change in property crime. These findings provide insights for the trajectory analysis of macro places (i.e. neighbourhood level). Consistent with the prior research of micro place trajectories (e.g., Weisburd et al., 2004; Groff et al., 2010; Curman et al., 2015), these findings confirmed two ideas: first, similar to micro places, neighbourhoods in the same city can experience disparate crime trajectories; second, the change in levels of citywide crime does not reflect the actual changes across neighbourhoods.

The existing research on crime and place has predominantly focused on examining the trajectory of crime in micro places and has typically overlooked what makes set of neighbourhoods belong to a certain group. Hence, the second aim of this study was to investigate whether factors that determine group membership are systemic or purely coincidence. A broad range of variables were brought together into a single model that examined their influence on group membership. This analysis reveals notable differences in terms of the influence of some variables on group membership. For example, some variables were found to reduce the probability of a neighbourhood being in one group, but the likelihood of being in the other group reduced by different variables. Similarly, some variables were found to increase the likelihood of being in a one group, but do not have an impact on the other group membership. These findings show that

the membership of different neighbourhood groups is influenced by different factors. This would appear to be consistent with our theory that posits there might be a systematic process that link similar neighbourhoods which could be the causal mechanisms that make them to have similar responses to external changes.

These findings, therefore, raise the question of whether these factors cause structural differences with the determinations of crime levels across neighbourhood groups which in turn may affect the way crime modelling should be approached. Thus, the third aim in this research was to explore whether the determinants of crime rates differ across groups of neighbourhoods. This possibility is supported by the results of the multiple regression analysis and the interaction test, which revealed that some neighbourhood characteristics showed different effects in different groups. As shown in the results, the effect of family disruption and business addresses showed a significant difference for group 2 in terms of the crime level compared to group 1. Also, similar results emerged from the poverty, where a significant difference was observed for both groups 2 and group 3 compared to group 1. In summary, while some variables showed a significant impact on the crime level, their effect was significantly different across groups. Although these analyses showed differences in the impact of some variables across clusters, the results should be interpreted with caution. A possible explanation is that these differences in variable impacts are a result of differences in crime opportunities across neighbourhoods (Weisburd et al., 2012). Additionally, consistent with our theory, these differences may reflect the existence of underlying factors which connect similar neighbourhoods and drive their crime trajectories and responses similarly to external factors, and we highlight this for future research.

A number of implications emerge from this research. At policy level, the clustering findings reinforce the importance of police and crime prevention strategies being different based

on crime development in clusters of neighbourhoods. If police become better at recognizing similar groups of neighbourhoods, they can develop more efficient strategies to address crime problems. This means that developing different police strategies and not relying on a single strategy for all neighbourhoods is more likely to increase the efficiency of police intervention and the allocation of crime prevention resources (Wheeler et al., 2016). Also, this study focused on a single type of crime (i.e., property crime) so other types of crime could follow different trajectories over time. Thus, the allocation of crime prevention resources strategies would benefit from the trajectory analysis and deal with neighbourhoods differently based on the trajectory clusters of crime types.

At a methodological level, the differences found in the impact of neighbourhood characteristics across groups have significant implications for the understanding of how we model crime data. The findings suggest that research concerned with addressing crime cannot rely on a single model that suggests universal causes of crime rates; more complex models are needed. Hence, the knowledge of crime trajectories and the systematic drivers of group membership has a significant effect on how we model crime data which could lead improvements in how we predict crime in the future. Furthermore, K-means algorithm was used in the clustering analysis as an alternative method to the GBTM that have been widely used in the trajectory clustering. Using K-means was useful in two ways. First, K-means does not require the data to be in a specific distribution and beats the GBTM in proc Traj in accommodating larger data (Curman et al 2015). Second, K-means statistics is available in most of the statistical analysis tools while the GBTM is limited to be in paid tools.

While this research provides a number of insights, it is subject to a number of limitations. The first of these concerns the difficulties encountered collecting crime data and neighbourhood characteristics over a number of years. The second is that the study did not examine the underlying

network of neighbourhoods due to the limitations of the methods used in the current research. Therefore, further research is required to build on the current study and to examine the possible underlying networks which connect neighbourhoods and drive the co-movement of crime by using a proper method for this purpose like social network analysis. In addition, this research focused on a single type of crime within one city. Therefore, to assess the generalizability of 3-step approach, future research should evaluate and confirm this method by applying it to data from different cities and other types of crime.

References

- Anderson, T. J. et al. (2016) '2016 Canadian Cardiovascular Society guidelines for the management of dyslipidemia for the prevention of cardiovascular disease in the adult', *Canadian Journal of Cardiology*. Elsevier, 32(11), pp. 1263–1282.
- Andresen, M. A., Curman, A. S. and Linning, S. J. (2017) 'The trajectories of crime at places: understanding the patterns of disaggregated crime types', *Journal of quantitative criminology*. Springer, 33(3), pp. 427–449.
- Andresen, M. A., Linning, S. J. and Malleson, N. (2017) 'Crime at places and spatial concentrations: Exploring the spatial stability of property crime in Vancouver BC, 2003– 2013', *Journal of quantitative criminology*. Springer, 33(2), pp. 255–275.
- Andresen, M. A. and Malleson, N. (2011) 'Testing the stability of crime patterns: Implications for theory and policy', *Journal of Research in Crime and Delinquency*. Sage Publications Sage CA: Los Angeles, CA, 48(1), pp. 58–82.
- Bannister, J., Bates, E. and Kearns, A. (2017) 'Local variance in the crime drop: A longitudinal study of neighbourhoods in greater Glasgow, Scotland', *The British Journal of Criminology*. Oxford University Press UK, 58(1), pp. 177–199.
- Baumer, E. et al. (1998) 'The influence of crack cocaine on robbery, burglary, and homicide rates: A cross-city, longitudinal analysis', *Journal of research in crime and delinquency*. SAGE Publications, Inc., 35(3), pp. 316–340.
- Bellair, P. E. and Browning, C. R. (2010) 'Contemporary disorganization research: An assessment and further test of the systemic model of neighbourhood crime', *Journal of research in crime and delinquency*. Sage Publications Sage CA: Los Angeles, CA, 47(4), pp. 496–521.

- Blokland, A. A. J., Nagin, D. and Nieuwbeerta, P. (2005) 'Life span offending trajectories of a Dutch conviction cohort', *Criminology*. Wiley Online Library, 43(4), pp. 919–954.
- Blokland, A. A. J. and Nieuwbeerta, P. (2005) 'The effects of life circumstances on longitudinal trajectories of offending', *Criminology*. Wiley Online Library, 43(4), pp. 1203–1240.
- Braga, A. A., Hureau, D. M. and Papachristos, A. V (2011) 'The relevance of micro places to citywide robbery trends: a longitudinal analysis of robbery incidents at street corners and block faces in Boston', *Journal of Research in Crime and Delinquency*. Sage Publications Sage CA: Los Angeles, CA, 48(1), pp. 7–32.
- Braga, A. A., Papachristos, A. V and Hureau, D. M. (2010) 'The concentration and stability of gun violence at micro places in Boston, 1980–2008', *Journal of Quantitative Criminology*. Springer, 26(1), pp. 33–53.
- Bushway, S. D., Sweeten, G. and Nieuwbeerta, P. (2009) 'Measuring long term individual trajectories of offending using multiple methods', *Journal of Quantitative Criminology*. Springer, 25(3), pp. 259–286.
- Byrne, J. M. and Sampson, R. J. (1986) 'Key issues in the social ecology of crime', in *The social ecology of crime*. Springer, pp. 1–22.
- Cohen, L. E. and Felson, M. (1979) 'Social change and crime rate trends: A routine activity approach', *American sociological review*. JSTOR, pp. 588–608.
- Cornish, D. B. and Clarke, R. V (1987) 'Understanding crime displacement: An application of rational choice theory', *Criminology*. Wiley Online Library, 25(4), pp. 933–948.
- Curman, A. S. N., Andresen, M. A. and Brantingham, P. J. (2015) 'Crime and Place: A Longitudinal Examination of Street Segment Patterns in Vancouver, BC', *Journal of Quantitative Criminology*, 31(1), pp. 127–147.
- Dietz, R. D. and Haurin, D. R. (2003) 'The social and private micro-level consequences of homeownership', *Journal of Urban Economics*. Elsevier, 54(3), pp. 401–450.
- Elragal, A. and El-Gendy, N. (2012) 'Trajectory data mining and the need for semantics', in *European, Mediterranean and Middle Easter Conference on Information Systems*, June, pp. 7–8.
- Felson, M. and Boba, R. L. (2010) *Crime and everyday life*. Sage.
- Forgy, E. W. (1965) 'Cluster analysis of multivariate data: efficiency versus interpretability of classifications', *biometrics*, 21, pp. 768–769.
- Galster, G., Cutsinger, J. and Lim, U. (2007) 'Are neighbourhoods self-stabilising? Exploring endogenous dynamics', *Urban Studies*. Department of Geography and Urban Planning, Wayne State University, 3198 Faculty/Administration Building, Detroit, MI 48202, United States, 44(1), pp. 167–185.
- Gelman, A. and Loken, E. (2013) 'The garden of forking paths: Why multiple comparisons can be a problem, even when there is no “fishing expedition” or “p-hacking” and the research hypothesis was posited ahead of time', Department of Statistics, Columbia University.
- Groff, E. R. and La Vigne, N. G. (2001) 'Mapping an opportunity surface of residential burglary', *Journal of Research in Crime and Delinquency*. Sage Publications, 38(3), pp. 257–278.
- Groff, E. R., Weisburd, D. and Yang, S.-M. (2010) 'Is it important to examine crime trends at a local “micro” level?: A longitudinal analysis of street to street variability in crime trajectories', *Journal of Quantitative Criminology*. Springer, 26(1), pp. 7–32.

- Harcourt, B. E. and Ludwig, J. (2006) 'Broken windows: New evidence from New York City and a five-city social experiment', *U. Chi. L. Rev. HeinOnline*, 73, p. 271.
- Hartigan, J. A. and Wong, M. A. (1979) 'Algorithm AS 136: A k-means clustering algorithm', *Journal of the Royal Statistical Society. Series C (Applied Statistics)*. JSTOR, 28(1), pp. 100–108.
- Hipp, J. R. (2007) 'Income inequality, race, and place: Does the distribution of race and class within neighbourhoods affect crime rates?', *Criminology*. Department of Criminology, Law and Society, University of California Irvine, 45(3), pp. 665–697.
- Keele, L. and Keele, L. (2008) *Semiparametric regression for the social sciences*. Wiley Online Library.
- Kinney, J. B. et al. (2008) 'Crime attractors, generators and detractors: Land use and urban crime opportunities', *Built environment*. Alexandrine Press, 34(1), pp. 62–74.
- Liu, S. (2015) 'Is the Shape of the Age-Crime Curve Invariant by Sex? Evidence from a National Sample with Flexible Non-parametric Modeling', *Journal of Quantitative Criminology*. Springer, 31(1), pp. 93–123.
- Loftin, C. and Hill, R. H. (1974) 'Regional subculture and homicide: An examination of the Gastil-Hackney thesis', *American Sociological Review*. JSTOR, pp. 714–724.
- MacQueen, J. (1967) 'Some methods for classification and analysis of multivariate observations', in *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*. Oakland, CA, USA, pp. 281–297.
- McPherson, M., Smith-Lovin, L. and Cook, J. M. (2001) 'Birds of a feather: Homophily in social networks', *Annual review of sociology*. Annual Reviews 4139 El Camino Way, PO Box 10139, Palo Alto, CA 94303-0139, USA, 27(1), pp. 415–444.
- de Melo, S. N., Matias, L. F. and Andresen, M. A. (2015) 'Crime concentrations and similarities in spatial crime patterns in a Brazilian context', *Applied Geography*. Elsevier, 62, pp. 314–324.
- Miethe, T. D. and Meier, R. F. (1994) *Crime and its social context: Toward an integrated theory of offenders, victims, and situations*. Suny Press.
- Nagin, D. S. (1999) 'Analyzing developmental trajectories: a semiparametric, group-based approach.', *Psychological methods*. American Psychological Association, 4(2), p. 139.
- Nagin, D. S. and Land, K. C. (1993) 'Age, criminal careers, and population heterogeneity: Specification and estimation of a nonparametric, mixed Poisson model', *Criminology*. Wiley Online Library, 31(3), pp. 327–362.
- Nagin, D. S. and NAGIN, D. (2005) *Group-based modeling of development*. Harvard University Press.
- Nieuwbeerta, P. et al. (2011) 'A life-course analysis of offense specialization across age: Introducing a new method for studying individual specialization over the life course', *Crime & Delinquency*. Sage Publications Sage CA: Los Angeles, CA, 57(1), pp. 3–28.
- Paternoster, R. and Bachman, R. (2001) 'Explaining criminals and crime', Los Angeles, CA: Roxbury.
- Pryce, G., Dean, N., Olnier, D., Woodcock, B. and Steele, K. (2018) *Crime Cascades: Social Network Analysis of Neighbourhood Crime Dynamics*, Presentation to South Yorkshire Police.
- Raleigh, E. and Galster, G. (2015) 'Neighbourhood Disinvestment, Abandonment, And Crime Dynamics', *Journal of Urban Affairs*. Data Driven Detroit, United States: Blackwell Publishing Ltd, 37(4), pp. 367–396.

- Sampson, R. J. and Groves, W. B. (1989) 'Community structure and crime: Testing social- disorganization theory', *American journal of sociology*. University of Chicago Press, 94(4), pp. 774–802.
- Sampson, R. J., Morenoff, J. D. and Gannon-Rowley, T. (2002) 'Assessing "neighbourhood effects": Social processes and new directions in research', *Annual review of sociology*. Annual Reviews 4139 El Camino Way, PO Box 10139, Palo Alto, CA 94303-0139, USA, 28(1), pp. 443–478.
- Sampson, R. J., Raudenbush, S. W. and Earls, F. (1997) 'Neighbourhoods and violent crime: A multilevel study of collective efficacy', *Science*. American Association for the Advancement of Science, 277(5328), pp. 918–924.
- Schuerman, L. and Kobrin, S. (1986) 'Community careers in crime', *Crime and justice*. University of Chicago Press, 8, pp. 67–100.
- Shaw, C. R. and McKay, H. D. (1942) 'Juvenile delinquency and urban areas.' University of Chicago Press.
- Sherman, L. W. (1995) 'Hot spots of crime and criminal careers of places', *Crime and place*. Willow Tree Press, Monsey, NY, 4, pp. 35–52.
- Sherman, L. W., Gartin, P. R. and Buerger, M. E. (1989) 'Hot spots of predatory crime: Routine activities and the criminology of place', *Criminology*. Wiley Online Library, 27(1), pp. 27–56.
- Weisburd, D. et al. (1992) 'Contrasting crime general and crime specific theory: The case of hot spots of crime', *Advances in criminological theory*. Transaction Press New Brunswick, NJ, 4(1), pp. 45–69.
- Weisburd, D., Bushway, S. and Lum, C. (2004) 'Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle', 42(2).
- Weisburd, D., Groff, E. R. and Yang, S.-M. (2012) *The criminology of place: Street segments and our understanding of the crime problem*. Oxford University Press.
- Weisburd, D., Morris, N. A. and Groff, E. R. (2009) 'Hot spots of juvenile crime: A longitudinal study of arrest incidents at street segments in Seattle, Washington', *Journal of Quantitative Criminology*, 25(4), pp. 443–467.
- Wheeler, A. P., Worden, R. E. and McLean, S. J. (2016) 'Replicating Group-Based Trajectory Models of Crime at Micro-Places in Albany, NY', *Journal of Quantitative Criminology*. Springer, 32(4), pp. 589–612.
- Wright, D. B. and London, K. (2009) *Modern regression techniques using R: a practical guide*. Sage.

CHAPTER 4

Do Crime Rates in Similar Neighbourhoods Move Together? Network Analysis of Spatial Proximity and Assortative Mixing in Neighbourhood Crime Dynamics

4.1 Introduction

In the previous chapter, I started the exploration of the interdependencies of crime dynamics between neighbourhoods and how these have material implications for how we understand crime. For example, there appeared to be structural differences in the determinants of crime between neighbourhood with different crime dynamics. This work follows in a long tradition of studying the spatial concentration of crime at different geographic scales (Bannister et al., 2018). Scholars have also begun to dissect crime trajectories and explore them at different scales and spatial units including street segments (Weisburd et al., 1992, Groff and La Vigne, 2001, Weisburd et al., 2012) and neighbourhoods (Byrne and Sampson, 1986, Schuerman and Kobrin, 1986, Bannister et al., 2018). Crime trajectory analysis is defined as being the study of long-term patterns of crime within a geographic unit (Weisburd et al., 2004, Weisburd et al., 2012).

In this chapter, I continue the investigation of neighbourhood interdependencies by exploring the structure of these inter-neighbourhood linkages. We can think of the neighbourhood interdependencies in crime dynamics as a network, where each neighbourhood is a node and the links between them represent co-movement of crime rates. My interest in this chapter is in the structure and drivers of these interdependencies. For example, is there evidence of homophily—also known as ‘assortative mixing’—in the co-movement of crime? In other words, are neighbourhoods that are similar in terms of their characteristics such as the levels of poverty and

ethnic mix more likely to have closely entwined crime trajectories? This could be important in terms of predicting how changes to neighbourhood characteristics might affect future crime trajectories. It may also help us come to a better understanding of the interconnectedness of crime: crime rates do not fluctuate in isolation, rather they are part of a complex web of spatial interdependencies. I am also interested in the role of geographical proximity: to what extent do neighbourhoods that are neighbourhoods together have crime rates that move together, and is there evidence of ‘social frontiers’ in crime? That is, will adjacent neighbourhoods with contrasting levels of affluence actually be more likely to have crime rates that move together because of the social conflict between such neighbourhoods?

Whilst a growing body of literature has recognised the importance of moving beyond a focus on the intra-neighbourhood setting to recognize the importance of connections between neighbourhoods, there has been little research on the structure of interdependencies. Neighbourhoods have been conceptualized as urban villages, with distinct social and spatial characteristics (Papachristos and Bastomski, 2018b). Park and Burgess (1925) argued that, regardless of spatial proximity, neighbourhoods can be connected by common values or separated by factors such as poverty, racial segregation, and more—the city acting as a “mosaic of little worlds which touch but do not interpenetrate” (Park and Burgess, 1925, p. 40). Yet, there are also clear conceptual precedents for thinking of neighbourhood through the lens of network theory. Sampson (2004) discussed the concept of neighbourhood networks and argued that it should not be limited by notions of social networks or personal relations, as “neighbourhoods are themselves nodes in a larger network of spatial relations” (Sampson, 2004). In the words of (Mears and Bhati, 2006), “communities do not exist in isolation ... they may affect and be affected by other communities with which they coexist and interact”.

Recent studies have argued that not only does spatial proximity promote criminogenic ties and the diffusion of crime, but that social proximity does so as well. Social ties are “spatially unbounded,” whereby individuals can be socially connected with others from distant areas through several channels (Wellman, 1999a, Mears and Bhati, 2006), such as focal institutions or even the general propensity to associate with other people like themselves (Papachristos and Bastomski, 2018b).

This work raises a number of salient questions. What causes changes in crime rates in one neighbourhood to be linked to crime changes in some neighbourhoods, while being disconnected from others? What makes two neighbourhoods’ crime rates move together, other than geographic proximity?

Apart from (Weisburd et al., 2012), the crime trajectory research to date has tended to focus on identifying geographic areas that experience similar crime trajectories and overlook the underlying mechanism driving those trajectories. In their comprehensive study, using logistic regression, (Weisburd et al., 2012) did identify what characteristics lead neighbourhoods to similar trajectories. However, there are major weaknesses in existing research which relies heavily on various forms of regression analysis to investigate inter-neighbourhood crime dynamics. This methodological approach to the data is problematic because it rests on the assumption that observations are either conditionally or unconditionally independent of one another. This makes regression less than ideal to say the least if the very purpose of the analysis is to estimate the degree of dependence between neighbourhoods (Dean and Pryce, 2017). Spatial econometric methods such as exploratory spatial data analysis and spatial regression models (Anselin et al. 2000) relax this assumption but only in a very specific and limited way; e.g. to allow for dependence between neighbourhoods that are contiguous or in close proximity. Distant neighbourhoods are assumed to

be unconnected. Distant neighbourhoods are assumed to be unconnected to one another. The standard spatial regressions are methodologically useful and used widely to study the crime diffusion and clusters (e.g., Meares and Bhati, 2006; Tita and Radil, 2010a, 2011). However, such models are imprecise to study the interdependency between neighbourhoods as “they model the diffusion of crime as if it spreads like an airborne pathogen” (Papachristos and Bastomski, 2018). Furthermore, the standard spatial regressions are useful in simply demonstrating and mapping the crime patterns more than explaining the causes of the crime clusters (Radil et al., 2010). Thus, relying on such models is considerably imprecise to explain the complicated intercommunity social processes driving crime patterns (Leenders, 2002). Therefore, if we want to understand how a range of factors might affect the likelihood of inter-neighbourhood linkages in crime dynamics, not just distance or contiguity, then we need to employ methods designed specifically for the analysis of networks.

However, despite the use of network language when talking about neighbourhoods and neighbourhood crime, as far as we are aware, network methods have yet to be applied in the literature on co-movement of crime. Whilst clustering neighbourhoods on the basis of similarity of crime trajectories – as in the previous chapter – these clusters remain a ‘black box’ in the sense that the much of the underlying structures of interdependence remain hidden. Spatial econometric approaches (Anselin et al. 2000) are of some value in identifying dependencies defined in terms of spatial proximity or contiguity, they overlook non-spatial dependencies arising from “assortative mixing” in non-spatial attributes. Such methods also comprehensively overlook the position of a node in the network – for example, how important the node is in the connectedness of the entire network (e.g. whether it has high levels of degree centrality or betweenness centrality).

Using network analysis to study the neighbourhood crime dynamics, the current study contributes to the literature by addressing some of the most prominent limitations of prior work: (1) previous research has focused on identifying similar crime trajectories and largely overlooked the impact of factors, such as social connections, that may connect similar areas; (2) empirical investigations into the underlying factors driving crime trajectories in similar but non-contiguous neighbourhoods are scarce and rely on inappropriate methods; (3) prior research into neighbourhood networks has largely focused on co-offending and gang networks rather than neighbourhood-level crime trajectories. To my knowledge, no previous research has used statistical network analysis to investigate why some neighbourhood crime rates move together. This omission is important not only for the methodological reasons noted above but also because network analysis offers a powerful conceptual framework for thinking about the co-movement of crime.

I focus in particular on the concept of “assortative mixing” (also termed homophily) and the extent to which it applies to the geographic units such as neighbourhood and their crime trajectories: i.e. whether similar neighbourhoods are more likely to be linked in terms of their crime dynamics. Identifying the potential drivers of crime co-movement between neighbourhoods is important because it will help to deepen our understanding of why neighbourhood crime rates move together.

This research uses crime trajectory data from Cleveland, Ohio (USA), between 2010 and 2017, and the US census data, to estimate a set of exponential random graph models which allow us to identify the attributes of neighbourhoods associated with crime co-movement. The results reveal significant effects of both social distance and spatial distance, indicating that both are key determinants of crime co-movement networks. In addition, we find a “social frontier” (Dean et

al., 2019) effect for crime dynamics: crime rates of contiguous neighbourhoods with markedly different levels of disadvantage are significantly more likely to move together than similar contiguous neighbourhoods.

The remainder of this chapter is structured as follows. The chapter begins with an overview of the existing literature regarding crime and place, and neighbourhood networks. This is followed by the conceptual framework. The subsequent sections describe the data, methods, and results. Finally, a conclusion provides a discussion of the main findings in addition to the implications and suggestions for future research.

4.2 Background

Much research has examined the geographic concentration of crime: why crime rates are higher in some neighbourhoods than in others. The pioneering work of Shaw and McKay (1942) on delinquency rates in Chicago over thirty years provided empirical evidence of the concentration of crime as well as the stability of high-delinquency areas. A large and growing body of related literature has since flourished, confirming these ideas at different geographic scales. For instance, using data on 29,849 crimes in Seattle, Washington, Weisburd et al. (2004) examined the trajectories of crime on street segments from 1989 to 2002. They identified a typology of eighteen different crime trajectories. While the city experienced a 24% decrease in the overall rate of crime, only 14% of the street segments experienced a decrease. Most street segments (84%) were stable, and in 2% of them, crime increased. A similar study conducted by Braga et al. (2010b) investigated the trajectories of gun violence in micro places in Boston, Massachusetts, between 1980 and 2008. Their findings show that 3% of the street segments and intersections were responsible for more than 50% of violent crimes. These longitudinal investigations have shown the trajectories of crime over time and how geographic areas in the same city can experience disparate crime trajectories.

They also have shown how the citywide crime changes could be largely driven by small fraction of geographic areas. However, relatively little attention has been paid to the underlying mechanisms that connect neighbourhoods with similar crime trajectories and which may be driving these co-dependencies.

More recent research has increasingly recognized the need to focus on context, namely the important role played by neighbourhood characteristics and social processes (i.e., social disorganization, social control, and collective efficacy) in different levels of crime within different neighbourhoods. Social organization theory, developed by Shaw and McKay (1942), asserts that informal social control is an effective inhibitor of neighbourhood crimes. Sampson et al. (1997) extended this theory to formulate collective efficacy theory, which describes the ability of neighbourhood and community residents to recognize their common values and maintain social control, promoting collective efficacy and enabling them to act as capable guardians. Strong collective efficacy appears strongly correlated with: (1) community social cohesion (Bellair and Browning, 2010), (2) residential stability (Sampson and Groves, 1989, Hipp, 2007), and (3) rates of home ownership (Dietz and Haurin, 2003). By contrast, weak collective efficacy (and high crime rates) is typically found in neighbourhoods with: (1) high levels of heterogeneity, (2) low economic status, (3) family disruption, and (4) high residential mobility (Sampson and Groves, 1989, Harcourt and Ludwig, 2006). Crucially, neighbourhoods with similar underlying community structures and vulnerabilities may respond in similar ways to exogenous shocks – many of which may be unobservable or at least unnoticed by researchers – causing crime rates to move in tandem. Co-movements of crime may therefore reflect deep underlying structural similarities between neighbourhoods.

There has also been growing awareness of the need to move beyond the focus on intra-neighbourhood dynamics, to recognize interdependence of neighbourhoods (Peterson and Krivo, 2009, Tita and Greenbaum, 2009). It has been found that crime rates diffuse spatially in ways that transcend neighbourhood boundaries (Blumstein and Rosenfeld, 1998, Cohen and Tita, 1999, Anselin et al., 2000, Baller et al., 2001, Morenoff et al., 2001, Sampson, 2012). For example, homicide rates in one neighbourhood were found to be influenced by homicides in surrounding neighbourhoods (Morenoff et al., 2001). Similarly, local delinquency rates were associated with racial compositions and transitions in adjacent neighbourhoods (Heitgerd and Bursik Jr, 1987). One study conducted by Zeoli et al. (2014), using homicide data over 20 years in Newark, New Jersey, shows a stable spatiotemporal diffusion process, where rising rates of homicides started in the city centre and disseminated southward and westward during the study period.

More recently, research has examined the extent to which neighbourhood crime connections occur through spatial proximity versus other characteristics such as social proximity. A study on co-offending networks in Maricopa County, Arizona, by Schaefer (2012), showed that social proximity contributes to the structure of criminogenic networks. He also found that neighbourhoods with similar demographic characteristics are more likely to be connected and share co-offending ties. Another recent study by Papachristos and Bastomski (2018b) examined how criminal co-offending connects different neighbourhoods in Chicago. The results confirmed the importance of spatial proximity in linking neighbourhoods. Nevertheless, co-offending ties were found commonly between neighbourhoods with similar social characteristics irrespective of the distance between them. However, whilst these studies provide important insights into the structures of co-offending ties, they do not investigate how these relate to the interdependencies in

crime dynamics at the neighbourhood level. As such, networks of neighbourhood co-movement of crime remain unexplored.

4.3 Conceptual Framework

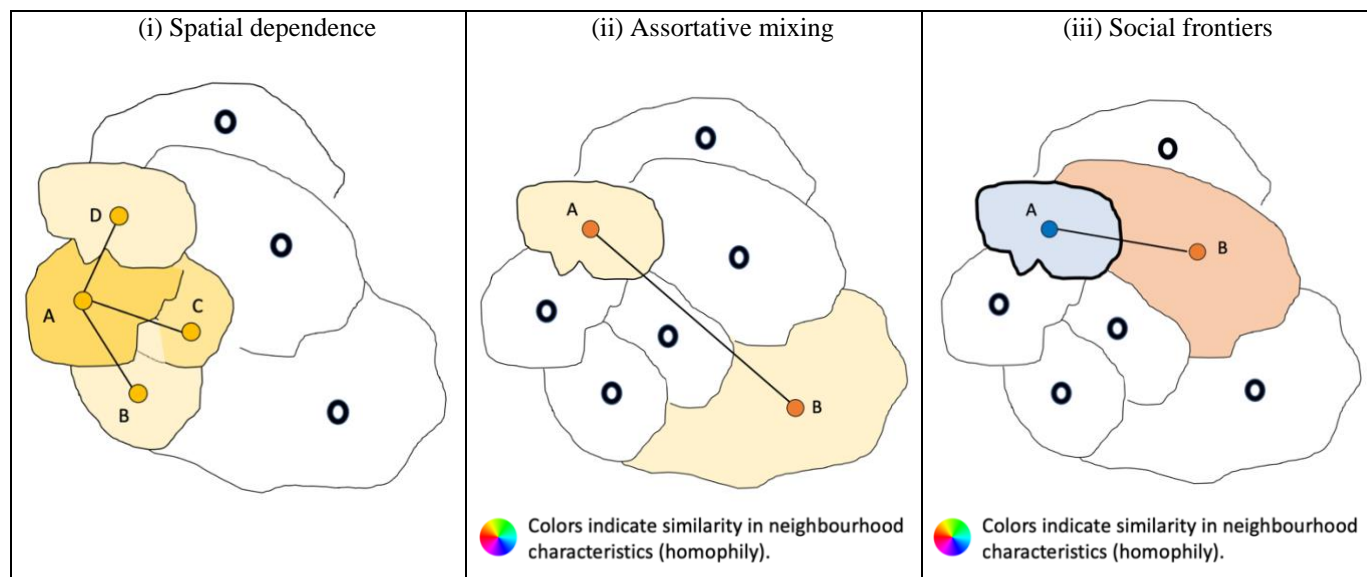


Figure 14 Conceptual framework

A considerable amount of literature has been published on criminology of place and has emphasized the concentrations and stability of crime over time in spatial units such as street segments and neighbourhoods. Despite these research efforts, the mechanisms driving neighbourhoods' crime co-movement have not been explored with methods that can accommodate assess the full range of potential dependencies between observational units. By using network theory, I think of the neighbourhood interdependencies in crime dynamics as a network, where each neighbourhood is a node and the links between them represent co-movement of crime rates. Hence, in this section, I develop a conceptual framework to understand the structure of inter-

neighbourhood connections and to explore the potential mechanisms (i.e., spatial dependence, non-spatial dependence (homophily), and social frontiers) drive neighbourhoods' crime co-movement.

(1) *Spatial dependence*. The form of dependence is shown graphically in the map of stylised neighbourhood depicted in Figure 14 panel (i), where the dots represent neighbourhood centroids which can also be thought of as nodes in a network, and the links between nodes represent co-movement of crime rates between a pair of neighbourhoods. The idea of spatial dependence shown by the links between neighbourhood A and its contiguous neighbours, B, C and D. Alternatively, the spatial dependence might be defined in terms of geographical distance with the closest neighbourhoods having the strongest levels of co-dependence in terms of crime trajectories. The theoretical rationale for this approach is Tobler's First Law of Geography: "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This has been borne out in the crime distribution literature which has shown that contiguity/spatial proximity is a crucial factor in explaining crime distribution. Crime rates in one neighbourhood are influenced by crime rates in surrounding neighbourhoods (e.g., Morenoff et al., 2001, Zeoli et al., 2014). In particular, previous studies indicating that disadvantage in geographically proximate neighbourhoods affects—or at least is very significantly associated with—crime rates and victimization in proximate neighbourhoods (Morenoff et al., 2001, Peterson and Krivo, 2009, Peterson et al., 2010, Crowder and South, 2011, Vogel and South, 2016). These findings are also in line with a previous study showing that crime rates may be affected by poverty in proximate neighbourhoods (Graif and Matthews, 2017). Thus, in the Cleveland data, we expect crime co-movement links are more likely to be formed between proximate neighbourhoods.

(2) *Non-Spatial dependence (homophily)*. The question raised by the spatial dependence literature is why should crime rates of contiguous/proximate neighbourhoods move together? Why

should Tobler's First Law of Geography apply to crime statistics? If we say that the reason is that neighbourhoods that are geographically close are more likely to be similar in terms of the drivers of crime such as deprivation, social and racial diversity, then we are using spatial proximity/contiguity as a crude proxy for these underlying variables, whilst excluding the possibility that similar but distant neighbourhoods also have high levels of co-dependence in terms of their crime trajectories. Indeed, recent studies have argued that not only does spatial proximity promote criminogenic ties and the diffusion of crime, but that social proximity does so as well. Social ties are "spatially unbounded," whereby individuals can be socially connected with others from distant areas through several channels (Wellman, 1999, Mears and Bhati, 2006), such as focal institutions or even the general propensity to associate with other people like themselves (Papachristos and Bastomski, 2018).

More recently, neighbourhood network research has examined the extent to which neighbourhood ties occur through spatial proximity versus other characteristics such as social proximity. As discussed earlier, the study of the co-offending networks in Maricopa County, by Schaefer (2012) found that social proximity contributes to the structure of criminogenic networks. In particular, he found that neighbourhoods with similar demographic characteristics are more likely to be connected and share co-offending ties. Another recent study by Papachristos and Bastomski (2018) examined how criminal co-offending connects different neighbourhoods in Chicago. The results confirmed the importance of spatial proximity in linking neighbourhoods. Nevertheless, co-offending ties were found commonly between neighbourhoods with similar social characteristics irrespective of the distance between them.

In the social network literature, the widely observed tendency for individuals to form ties with similar individuals (versus dissimilar individuals) is described as "assortative mixing" or

“homophily”. The similarity can be defined by culture, race, gender, social background, similar life experiences and socioeconomic resources. McPherson et al. (2001) describe homophily as “the principle that a contact between similar people occurs at a higher rate than among dissimilar people” (p. 416). This tendency towards homophily at the individual level increases the likelihood that friendships and criminal connections are more likely to emerge between similar neighbourhoods which are likely to similar life experiences and social backgrounds for their respective residents.

Through the lens of homophily theory, I propose two possible complementary explanations for the co-movement of crime. The first is that neighbourhoods with similar underlying community structures and vulnerabilities may respond in similar ways to exogenous shocks causing crime rates to move in tandem. For example, if crime in neighbourhoods A and B is primarily caused by disadvantage, the national cuts in welfare spending may affect crime rates in both neighbourhoods in a similar way. Similarly, if the lack of resources and neighbourhood inequality are the causes of crimes in these neighbourhoods, the investment in the core community institutions that are necessary elements for the collective life may cause the similarity in the crime rates in these neighbourhoods. Thus, co-movements of crime may reflect deep underlying structural similarities between neighbourhoods.

The second explanation is that, as raised in chapter 2, there are networks of information that link the neighbourhoods through which innovation about crime, crime opportunities, trends in violence, etc. are transferred through information cascades (Pryce et al., 2018). These networks may be formed through crime families and gangs that have a presence in multiple neighbourhoods. There may be networks of connections between different crime gangs formed through alliances, common friendships, time in prison together, etc. They also are linked through school friendships,

commuting flows, trade links in crime. Such networks are more likely to emerge between similar neighbourhoods because “social networks tend to be homophilous” (McPherson et al., 2001, p. 416). Both of these theories, if true, would suggest systematic drivers of the co-movement of crime.

In summary, homophily means that nodes are more likely to be connected if they are similar. As shown in Figure 14 panel (ii), neighbourhoods A and B are similar in some important characteristic such as poverty rates, and are therefore likely to be connected in terms of co-movements of crime, but they are not geographically contiguous. The same nodes' colour indicates a similarity between neighbourhood A and B in terms of their attributes (e.g., demographic, socioeconomic, etc). Thus, if neighbourhood A and B are said to be homophilous, it means that neighbourhoods A and B are more likely to be connected in terms of co-movement of crime if they have similar attributes.

(3) *Social frontiers*. In theories (1) and (2) above, the underlying conceptual driver of co-movements in crime between neighbourhoods is their similarity. However, there are reasons to believe that in some situations the opposite may be true; that contrasting neighbourhoods in close proximity may be more likely to experience inter-group conflict and this may cause a malignant connection to emerge between two adjacent neighbourhoods that drives co-movements in crime. This kind of contrast-connection could arise, for example, when an affluent neighbourhood is bordered by a deprived one. Relative deprivation theory (RDT) provides a potentially useful theoretical framework to understand the conflict that can arise from proximate inequality (Džuverovic, 2013). RDT focuses on the socio-psychological characteristics of individuals and emphasized the frustration they feel as a result of the difference between the actual and expected circumstances that become an essential motivation for violence (Dollard et al. 1939). According to RDT, a person or group's subjective dissatisfaction is caused by their relative position to another

person or group's situation or position (Gurr, 1970). Relative deprivation is therefore present when a person or group lacks the resources to maintain the standard of living, activities, and luxuries to which they are accustomed or which are generally supported by the society to which they belong (Runciman, 1966). Due to the social pressure, individuals' tendency to continually compare their own situation with the situation or position of the rest of society increases if this is not attainable.

In order to address the overlooked spatial structure of economic inequalities in the segregation, Iyer and Pryce (2022) develop a theory of 'social frontier' as a conceptual foundation to understand the effect of spatial discontinuities between neighbouring communities. Iyer and Pryce (2022, p. 2) describe the social frontiers as “clear-cut boundaries with relatively high edge intensity in a particular socio-demographic dimension.” Hence, social frontiers present at the boundaries between neighbouring communities where the gradient in such dimensions rises or declines abruptly that ultimately affect the exacerbating territorial conflict and social tension.

Accordingly, contrasting neighbourhoods in other dimensions of residential mix may also be linked through social tensions, rivalry and territoriality. The relative deprivation literature (e.g., Džuverovic, 2013, Dollard et al. 1939, Kawachi et al., 1999) has long argued that inequalities in wealth and income can be a source of social tension and crime. However, this literature has often overlooked the spatial structure of economic inequalities, and how the impact of relative deprivation on crime may lead to particular types of inter-neighbourhood crime rate dependencies. Iyer and Pryce (2022) for example, have argued that marked relative deprivation between contiguous neighbourhoods could give rise to a type of “social frontier” which heightens territorial behaviour and inter-group conflict. As a result, we may see the opposite of a homophily effect where contiguous neighbourhoods with marked differences in affluence have similar crime

dynamics due to this conflict. However, to my knowledge, this effect has yet to be studied empirically within the more capacious framework of network analysis.

Thus, I explore whether there is evidence of “social frontier” effects (Dean et al., 2019 ; Legewie, 2018; Legewie and Schaeffer, 2016)—i.e. whether crime rates are more likely to move together when contiguous neighbourhoods have sharply contrasting levels of disadvantage. It may be, for example, that when crime rates go up in a deprived neighbourhood, they also go up in a neighbouring affluent neighbourhood which is a primary target of criminal activity. This may be because targeting well-healed addresses yields greater financial returns and/or because higher levels of relative deprivation invoke greater inter-group social tensions and resentment.

Figure 14 panel (iii) represent the social frontier between contiguous neighbourhoods. The bold borders indicates to the social frontier between neighbourhoods A and B and the counteractive colours reflect the markedly different levels of disadvantage between neighbourhoods A and B.

4.4 Methods

4.4.1 Study Location

This study uses data on Cleveland, the second largest city in the state of Ohio (population 383,793). It is in north-eastern Ohio, at the mouth of the Cuyahoga River. It is of interest as an example of a high crime area. For example, its 2017 crime rate was 786 crimes per 100,000 people, 2.8 times greater than the national average and higher than 98.9% of US cities (City-data.com, 2017). Although the 2017 the crime rate (per 100,000) was 21% less than the rate in 2010 (the beginning of the study period), it remains 172% higher than the US national crime rate. It was also selected because of the availability of crime data. Cleveland is ethnically diverse, providing no shortage of variation in residential composition which is useful for modelling

purposes. According to the Census Bureau (2017), the racial composition of Cleveland was as follows: around 50% of Cleveland residents are Black or African Americans, 40% are White, with the remainder of mixed or other racial heritage.

4.4.2 Crime Data

Property crime data were obtained from the Northeast Ohio Community and Neighbourhood Data for Organizing (NEOCANDO), a data tool developed by the Centre on Urban Poverty and Community Development at Case Western Reserve University. The data are the property crime rates (burglary, vehicle theft, arson, and larceny) per 1000 for each census tract for 2010–2017. A census tract is an area established by the Census Bureau as roughly equal to a neighbourhood, with a population of 1200 to 8000. They have been used to represent neighbourhoods in many ecological studies of crime (e.g., Krivo and Peterson, 1996, Morenoff and Sampson, 1997, Schaefer, 2012). There are 175 census tracts in the city of Cleveland (of which 169 were included in the analysis, after outliers were excluded).

4.4.3 Neighbourhoods' Networks

In this analysis, a network of neighbourhoods is defined by the co-movement of crime. Neighbourhood A and B are said to be linked if there is a relationship between their crime trajectories. The network therefore consists of nodes (neighbourhoods) and the edges which link them. A link is said to occur between 2 nodes if there is a high correlation over time in their crime rate dynamics.

Let $G(V,E)$ be an undirected network, where V is the set of neighbourhoods in the city and E is the set of edges. The links between neighbourhoods can be summarized using an adjacency matrix, C , the elements of which represent the pairwise crime trajectory correlation between i and

j. An edge between two nodes *i* and *j* exist if the crime rate of neighbourhoods *i* and *j* move together (i.e., crime co-movement). The measure of the crime co-movement is denoted C_{ij} , so that an edge is said to exist between *i* and *j* if C_{ij} is greater than N , where N is the threshold for the correlation of crime rates. The threshold selection was based the stability of model results (i.e., stability of variable coefficients). Hence, the threshold selection began from a base threshold of 0.50, with the value of correlation incrementally increased until the best fitting model was found. The model results show stability in the range of 0.50-0.65 and threshold 0.65 was selected to build the network.

4.4.4 Exponential Random Graph Models (ERGMs)

The Exponential family is a family of statistical models for many types of data and the Exponential random graph models (ERGMs) is a statistical model for analysing social network. In social network analysis, there are several metrics and measurements exist to describe the structure of an observed network like density, betweenness, centrality, etc. These metrics, however, characterise the observed network, which is just one of many possible alternative networks. The structural properties of this group of alternative networks may be similar or dissimilar. In other words, the observed network is thought to be one of many possible networks formed by an unknown stochastic process that models potential network links as a random variable (Wasserman and Pattison, 1996). Thus, the aim of an ERGM is to examine the factors that influence tie formation between nodes. Thus, ERGM provide a model for statistical inference for network structure and the processes influencing the existence (and absence) of network ties. The model takes the network as a graph constituted by nodes and edges (ties) between nodes and examine the factors that influence ties formation between nodes. Thus, due to the relational nature of network data, ERGM violates the assumptions of independence of standard statistical models such as linear

regression (Contractor, Wasserman and Faust, 2006; Harris, 2014). Such models assume that each unit of observation in the data (in this case, neighbourhoods) is independent from all others. The conditional independence assumption is clearly problematic if we are interested in what determines the inter-neighbourhood dependence of crime dynamics as it precludes the very phenomenon we are seeking to study. ERGMs are theory driven so researchers need to consider the complex theoretical reasons for the emergence of social links in the observed network.

The basic ERGM takes the form:

$$pr(X = x) = \left(\frac{1}{k}\right) exp\left\{\sum_A \eta_A g_A(x)\right\}$$

The model specifies the probability of a set of ties, X , for all possible nodes with node features, dyad attributes, and observed network statistics (Lusher et al., 2013; Robins et al., 2007). g_A is a vector of network statistics, η_A is a vector of corresponding coefficients, and A indexes multiple statistics in $g(x)$. The variable k is a normalizing constant for the distribution. ERGM packages in R were used for all models (Hunter et al., 2008).

4.4.5 Variables

Following Papachristos and Bastomski (2018) and Schaefer (2012), several measures of neighbourhood characteristics established as important in the neighbourhood networks were obtained from 2010 US census data. These measures include: (1) neighbourhood disadvantage (percentage of families receiving food assistance and percentage of residents over 16 who are unemployed); (2) non-white (percentage of residents who are Black, Hispanic, Native, and mixed race); (3) residential instability (percentage of households that resided elsewhere five years prior to 2010 and the percentage of renter-occupied housing); (4) percentage of single-parent families

with children; (5) the historical redlining maps³ as shown in figure 5; (6) spatial proximity measured in miles using the geographic distance between neighbourhood centroids; (7) the existence of social frontiers, defined as sharp differences between adjacent neighbourhoods in racial, demographic, religious or socioeconomic characteristics (Dean et al., 2019). We estimated the existence of social frontiers by indexing the neighbourhoods from A_1 to A_n where n is the total number of neighbourhoods in the study area. A matrix Z denote the interaction between neighbourhood contiguity and social frontier of disadvantage calculated in terms of the absolute difference in disadvantage between neighbourhoods. The absolute difference in disadvantage between each pair of neighbourhoods is denoted as D_{ij} . Hence, following the methods used in (Dean et al., 2019), neighbourhoods i and j would have a social frontier if they were contiguous and D_{ij} is greater than S , where S is a threshold of one standard deviation from the mean of absolute difference in disadvantage. Descriptive statistics are presented in Table 5.

Table 5 Census tract descriptive statistics (N = 169)

	Median	Mean	St. Dev.
Disadvantage	24.65	25.16	11.80
Non-white	62.89	57.61	37.10
Resident instability	45.58	45.52	15.42
Single parent households	67.71	66.52	23
Total population	2311	2383.11	967.60

³ The term “redlining” or “redlined neighbourhoods” dates from the 1930s, when the Home Owners’ Loan Corporation (a federal agency) and lenders classified neighbourhoods on the basis of housing and demographic characteristics such as race and ethnicity of residents, home or rental value, residents’ occupations in 239 US cities. This classification graded neighbourhoods in terms of lending risk and was represented by colours where red was the riskiest. Residents of redlined neighbourhoods had difficulty accessing financial services such as mortgages, loans, and insurance. That is, access to financial services was based on an individual’s location instead of that individual’s qualifications.

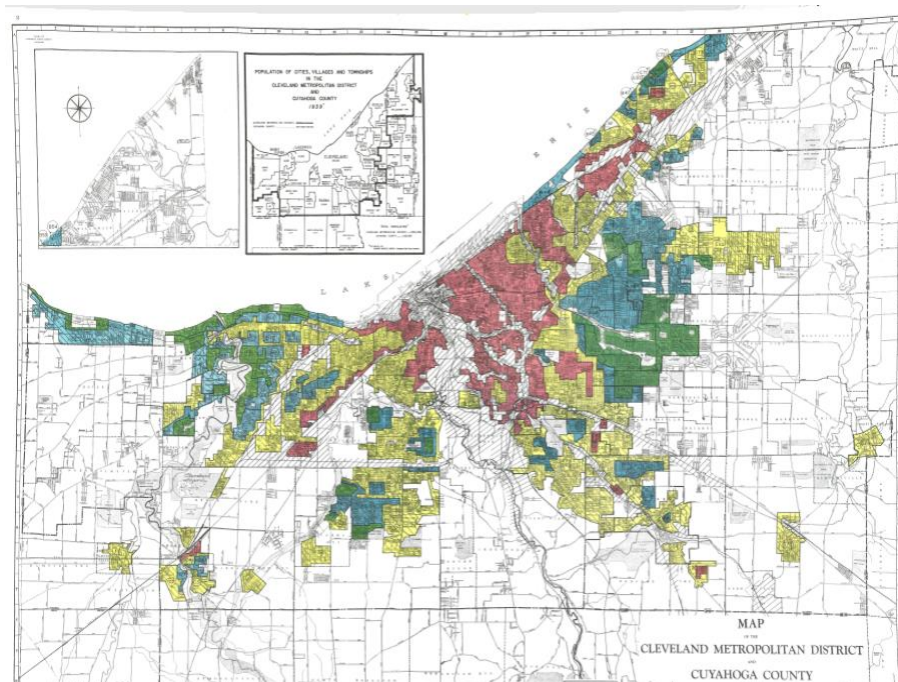


Figure 15 Cleveland Neighbourhoods 'Redlined' on the 1930s map

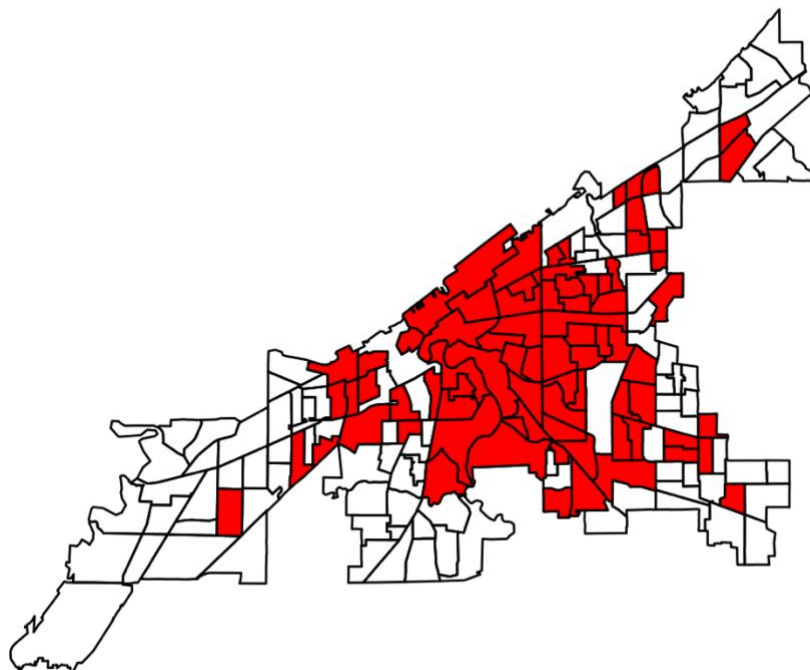


Figure 16 Cleveland Neighbourhoods 'Redlined' on 2010 map

4.4.6 Analytic Strategy

The analysis has two stages.

Stage (1): Descriptive analysis. This stage examines the distribution of the crime co-movement ties across neighbourhoods. The objective of this stage is to understand the degree to which crime co-movement ties are explained by spatial proximity and to uncover the structure of such a network.

Stage (2): Network modelling. After showing the patterns of the crime co-movement ties in the first stage, a series of Exponential Random Graph Models ERGMs were employed to examine the impact of social distance, spatial proximity, and spatial dependence (in the form of historical redlining) on tie formation. The objective of this stage is to determine (i) the extent to which homophily explains the underlying relationships between neighbourhoods, (ii) how this affects the formation of crime co-movement ties between neighbourhoods, and (iii) the most relevant characteristics of neighbourhoods in suggesting homophily between pairs of neighbourhoods. The purpose of this stage is to examine the factors that influence crime co-movement tie formation between nodes (i.e., neighbourhoods).

A series of ERGMs were estimated to examine what causes two neighbourhoods to be linked, or the impact of homophily on the formation of crime co-movement ties, by examining the impact of social distance, spatial proximity, the historical impact of redlining maps, and social frontiers. Social distance is the extent of dissimilarity between neighbourhoods in terms of disadvantage, Non-white, residential instability, and single-parent families. It was calculated through the absolute difference on the neighbourhood characteristics for all possible dyads in the network. Spatial proximity is defined as spatial distance and was constructed by calculating the number of miles between neighbourhood centroids. The redlining measure examined how likely

it was that two neighbourhoods were connected if both had been historically redlined. Social frontiers were included to further investigate the impact of social distance between contiguous neighbourhoods. The contiguity was coded as a contiguity matrix, where the cell was 1 if two neighbourhoods' boundaries touched at any point and 0 otherwise.

Statnet package in R was used for all analyses (Handcock et al., 2008). Models were estimated as follows. The first model was estimated as a control model that examined how neighbourhood's features were associated with crime co-movement ties to other neighbourhoods, but not examining the impact of social and spatial distance. Next, to examine the effect of spatial and social distances and their independent contribution to the model, spatial distance was added to the second model and social distance was added to the third model. Model 4 added the social frontier variable to examine the impact of social frontier and the disadvantage spillover effect. Then, both distances were added to model 5 to determine whether both distances are important for tie formation. Model 6 incorporated the redlining variable to test for long term spatial dependence (path dependency). All variables were included in model 7. AIC was used to assess each model's improvement to determine the contribution of each dimension to explain the network structure.

4.5 Results

4.5.1 Descriptive Analysis (ego-network) Results

Simply visualizing crime co-movement ties between neighbourhoods masks the long reach of ties that extend beyond geographically proximate neighbourhoods and, in so doing, ignores how far any single neighbourhood's ties reach across the city. As an example of how any particular neighbourhood's pattern of ties may or may not extend beyond local geography, consider Figure 17 which represents the ego networks of crime co-movement ties for three different

neighbourhoods. The term “ego network” here refers to each neighbourhood’s spatial patterning of co-movement ties—that is, those neighbourhoods (alters) to which the focal neighbourhood (“ego”) is directly connected and the ties among those alters. These three maps show the ego networks of neighbourhoods where ties reach to (A) the largest average distance across the city, (B) the average distance, and (C) the smallest average distance.



Figure 17 Ego networks for neighborhoods that their crime co-movement ties reach to the largest average, the average, and the smallest average distance across the city.

As the map shows, neighbourhood A has ties (i.e. crime co-movement ties) with 20 other neighbourhoods in the city, most of which are geographically distant. The average distance between neighbourhoods in the network is 5.31 miles. Neighbourhood A has the largest average distance, at 10.11 miles, that is, neighbourhood A has ties with neighbourhoods that are 10.11

miles apart. Neighbourhood B has connections with 21 other neighbourhoods across the city. Similar to neighbourhood A, most of those connections are with geographically distant neighbourhoods. Neighbourhood's B ties traverse an average of 5.31 miles. Finally, neighbourhood C has links to three different neighbourhoods; one is adjacent and the other two are proximate. Neighbourhood C's ties traverse the smallest average geographic distance, at 2 miles.

Although this descriptive analysis shows only three neighbourhoods out of 169, the purpose of these ego-network descriptive maps was to emphasize that neighbourhood networks are not always a function of geographical proximity and have undermine the reliance on simple formulations of spatial dependence assumed in some econometric models. As shown in Figure 8, most of the three neighbourhoods' ties are to distant neighbourhoods across the city. So, these results show that the spatial distance alone is insufficient to explain the crime co-movement ties and raises the question of what other factors contribute to the formation of crime co-movement network. I now move to the second stage of the investigation to explore this question explicitly using ERGMs.

4.5.2 Exponential Random Graph Model (ERGM) Results

Table 5 presents the results of a series ERGMs of the impact of social and spatial distance on the formation of crime co-movement ties between neighbourhoods. The first model is the baseline model. It includes the neighbourhoods' characteristics expected to impact the formation of crime co-movement ties. Model 1 includes node covariates for neighbourhood disadvantage, non-white, residential instability, and single-parent households. As shown in Table 6, residential instability has a positive impact, indicating that neighbourhoods with higher proportion of residential instability are more likely to display crime co-movement ties. By contrast, Non-white

reduces the probability of crime co-movement ties. The edges term is negative, which is normal in ERGMs and shows that, overall, ties are less likely to exist than not exist in this network.

Model 2 evaluates the impact spatial distance between neighbourhoods on the formation of ties. The significant negative effect of the physical distance reveals the importance of spatial proximity between neighbourhoods on ties. On average, the larger the distance between neighbourhoods, the smaller the likelihood of crime co-movement ties. The AIC is better than in the baseline model.

Model 3 includes several edge covariates that evaluate the impact of homophily on the formation of ties by examining the social distance between neighbourhoods. The impact of homophily was calculated as the absolute difference between each pair of neighbourhoods in levels of disadvantage, non-white, residential instability, and the proportion of single-parent families. As shown, three measures of social distance show a significant impact on the formation of ties between neighbourhoods. Except for disadvantage, the negative effects of social measures indicate that social dissimilarity between neighbourhoods reduces the probability of ties, meaning that similar neighbourhoods (in terms of social characteristics) are more likely to be linked.

In particular, the effects of residents' instability and the proportion of broken families are particularly large, indicating that neighbourhoods with similar levels of residential instability and broken families are significantly more likely to experience similar trajectories of crime. The level of disadvantage also has a significant effect on tie formation between neighbourhoods. However, an unanticipated effect direction deserves further investigation, which is carried out in the next set of models. Nevertheless, this model shows a better AIC than the baseline model, indicating that this model fits the data better.

Table 6 Coefficients and standard errors from exponential random graph models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
edges	-2.058*** (0.133)	-1.832*** (0.144)	-1.833*** (0.167)	-1.883*** (0.168)	-1.798*** (0.173)	-1.912*** (0.148)	-1.887*** (0.178)
Disadvantage	-0.044 (0.026)	-0.057* (0.027)	-0.101*** (0.029)	-0.101*** (0.029)	-0.108*** (0.029)	-0.055* (0.027)	-0.106*** (0.029)
Non-white	-0.11* (0.043)	-0.115** (0.043)	-0.049 (0.049)	-0.055 (0.049)	-0.067 (0.049)	-0.113** (0.043)	-0.066 (0.049)
Resident instability	0.191*** (0.023)	0.182*** (0.023)	0.207*** (0.023)	0.205*** (0.023)	0.199*** (0.024)	0.184*** (0.023)	0.2*** (0.024)
Single parent families	-0.0004 (0.001)	-0.0004 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.0003 (0.001)	-0.001 (0.001)
<i>Spatial distance</i>							
Spatial distance		-0.152*** (0.038)			-0.092* (0.045)	-0.144*** (0.038)	-0.085* (0.045)
<i>Social distance</i>							
Disadvantage			0.186*** (0.039)	0.188*** (0.039)	0.191*** (0.039)		0.194*** (0.039)
Non-white			-0.118 (0.072)	-0.103 (0.072)	-0.083 (0.072)		-0.081 (0.072)
Resident instability			-0.108** (0.037)	-0.1** (0.037)	-0.095* (0.037)		-0.092* (0.037)
Single parent families			-0.005*** (0.002)	-0.005*** (0.002)	-0.005** (0.002)		-0.005** (0.002)
Social frontier				0.527*** (0.147)	0.359* (0.168)		0.353* (0.168)
Redlining						0.124* (0.054)	0.123* (0.054)
AIC	9739	9725	9713	9703	9701	9722	9698
<i>Note:</i> *p<0.05 **p<0.01 ***p<0.001							

In order to further investigate the effect that two neighbourhoods are more likely to be linked if they have different level of disadvantage, the contiguity effect was examined in model 4. This was to determine whether there is a positive effect of relative neighbourhood: i.e. that co-movement of crime is more likely if neighbourhoods i and j form a social frontier (Dean et al., 2019). The results show an effect similar to the previous model, indicating that advantaged neighbourhoods are indeed more likely to experience crime movement similar to disadvantaged neighbourhoods if they are contiguous.

Model 5 incorporates both spatial and social distance to determine whether both distances are important for tie formation. Comparing the AIC to the previous model shows that including both distances in one model fits better than only including one; in other words, both are important in explaining the crime co-movement network structure.

Model 6 removes the measures of social distance and includes redlining to evaluate the long-term effects of redlining maps on the formation of crime co-movement ties between neighbourhoods. The results show a significant positive effect, indicating that historically redlined neighbourhoods are likely to have similar crime trajectories. In other words, the crime rates of two neighbourhoods are more likely to move together if both neighbourhoods were once redlined. This suggests that historical patterns of discrimination and disadvantage may have established path dependency that still have implications for crime dynamics today.

Lastly, model 7 incorporates all effects - redlining, social distance, and spatial proximity - to establish whether the effect still hold when they are included in the same model. All show persistently significant effects. Similar to Model 3, the largest magnitude of social distance effect is shown in disadvantage and residential instability. The model also has the best AIC, indicating that all three measures are important in explaining the crime co-movement network.

Taken together, these results yield the following key insights. First, the effect of spatial proximity is robust in all models, indicating that this is key for property crime co-movement between neighbourhoods. Interestingly, neighbourhoods with a higher level of disadvantage are more likely to experience crime trajectories similar to advantaged neighbourhoods. In other words, similarity in disadvantage level reduces the likelihood of crime co-movement ties between neighbourhoods. However, in examining what causes similar crime trajectories in dissimilar neighbourhoods, contiguity appears to be the potential driver. Second, the model with the best fit

included all measures together, indicating that redlining, spatial and social distances are all key determinants of crime co-movement networks.

4.6 Discussion

Extensive research has been carried out on neighbourhood crime trajectories over the past 80 years. However, there is still very little understanding of neighbourhoods' interdependencies beyond the role of geographical proximity. Prior research has emphasized the spatial clustering and stability of crime trajectories over time in spatial units such as street segments and neighbourhoods. However, the mechanisms driving neighbourhoods' crime co-movement have not been explored using statistical methods that permit dependency between observational units. Using network theory as a conceptual framework for thinking about co-movement of crime across neighbourhoods has enabled the analysis to be framed in a way that makes the research questions amenable to statistical network methods. This is the first study I am aware of that explicitly investigates the range of factors that drive the co-movement of crime between neighbourhoods and does so using appropriate methods.

Although previous research has investigated the neighbourhood connections and the factors that foster ties between neighbourhood crime rates, the main focus was on the co-offending networks. Thus, I have sought to extend this literature by looking at the network of the crime co-movement and, more importantly, by exploring the underlying mechanisms driving similar crime trajectories across neighbourhoods. The findings of this research indicate that two neighbourhoods are more likely to be linked if they are spatially close. However, spatial proximity was not the only factor affecting the formation of ties between neighbourhoods. My results show that neighbourhoods that are similar in terms of residential instability and broken families are more likely to be linked.

Interestingly, the findings also show that the heterogeneity in the level of disadvantage increases the likelihood of crime co-movement ties between contiguous neighbourhoods. I find that the disadvantage level in a given neighbourhood has a significant impact on the formation of ties with other neighbourhoods in terms of crime dynamics. However, in contrast to co-offending network research (Schaefer, 2012, Papachristos and Bastomski, 2018b), the results show that the similarity in the disadvantage level reduces the probability of ties formation between neighbourhoods. That is, ties are more likely to exist between neighbourhoods with a dissimilar level of disadvantage, indicating patterns of heterophily in tie formation. There are several possible explanations for this. First, disadvantaged neighbourhoods may be tied in terms of crime co-movement with advantaged neighbourhoods because of the lack of resources in the disadvantaged areas (Small and McDermott, 2006, Murphy and Wallace, 2010, Tran et al., 2013) and the disadvantage in work communities (Graif et al., 2017). Second, the links between neighbourhoods with a dissimilar level of disadvantage may be because of social frontier effect between contiguous neighbourhoods or spillovers of disadvantage to proximate neighbourhoods. To further explore this relationship, an additional model was defined to control for contiguity and measure the effect of the social frontier. The positive significant effect remained stable even after controlling for the contiguity, indicating that these links are more likely to exist due to the effects of social frontier or spillovers of disadvantage. This finding is consistent with previous research confirming the effect of disadvantage in geographically proximate neighbourhoods on the crime rates and victimization in a neighbourhood (Morenoff et al., 2001, Peterson and Krivo, 2009, Peterson et al., 2010, Crowder and South, 2011, Vogel and South, 2016). These results are in line with those of previous studies showing that crime rates are affected by poverty in proximate neighbourhoods (Graif and Matthews, 2017). These findings are also in line with previous research that found a social frontier

is associated with higher crime rates in dissimilar neighbourhoods (Hirschfield et al., 2014, Dean et al., 2019). Consistent with Iyer and Pryce (2022) argument that marked relative deprivation between contiguous neighbourhoods could give rise to a type of “social frontier” which heightens territorial behaviour and inter-group conflict. As a result, we may see the opposite of a homophily effect where contiguous neighbourhoods with marked differences in affluence have similar crime dynamics due to this conflict.

Another important finding was that crime co-movement ties were more likely between neighbourhoods that were classified as redlined. This finding broadly supports earlier work that found an association between redlined neighbourhoods and increased crime rates in three different cities (Anders, 2019). These associations may be the result of several different path dependency mechanisms. The historical redlining of neighbourhoods was based on criteria such as location, disadvantage, and the proportion of residents of a racial minority (Anders, 2019). The long-term effects of this stigma have contributed to racial segregation, lower income and educational attainment, which are in turn associated with increased crime rates (Billings et al., 2014, Anders, 2019). Thus, redlining may capture a range of persistent and self-replicating vulnerabilities that lead crime rates in these neighbourhoods to respond in similar ways to exogenous shocks, resulting in close co-movements in crime rates over time. These vulnerabilities may be complex and multi-faceted and difficult to anticipate *a priori*. For example, redlined-based homophily in crime trajectories may reflect the structural isolation of redlined neighbourhoods. Ex-offenders struggle to find jobs and housing options, which leads them to stay in their previous neighbourhoods or move to similarly disadvantaged neighbourhoods (La Vigne, 2003, Kirk, 2009), which leads to fewer ties to other communities and a web of underlying social connections between redlined areas.

4.7 Conclusion

These findings have important implications for policy, theory and methods. First, they suggest that crime dynamics in a given neighbourhood are affected by spatial proximity regardless of the level of disadvantage. That is, advantaged neighbourhoods are more likely to experience crime trajectories similar to the disadvantaged neighbourhoods if they are contiguous. Therefore, policies and interventions may be less effective if neighbourhoods are treated in isolation from other neighbourhoods. That is, the focus on the disadvantage level in one neighbourhood may be insufficient to reduce the crime rates if the connected neighbourhoods are overlooked. On the other hand, paying attention to a disadvantaged neighbourhood with more connections may help to reduce crime rates in larger areas (Graif et al., 2021).

Second, the findings advance disadvantage theory by showing that a given level of disadvantage is not only associated with higher crime rates in local neighbourhood but also in contiguous areas. Also, this research shows for the first time how social frontiers may drive crime co-movement across neighbourhoods, confirming the impact of social frontiers on crime rates (Dean et al., 2019) which to my knowledge has not been studied empirically within the more capacious framework of network analysis.

Third, in contrast to previous research on the dynamics of crime, this research has demonstrated how crime trajectory analysis can be conceptualize using network theory and this framework leads naturally to a more robust statistical approach for understanding the underlying mechanisms driving the dynamics of crime.

This research is not without limitations. First, whilst the findings provide evidence of the homophily effect on the formation of crime co-movement ties, it is difficult to fully explain the meaning of those connections due to the limitations of the data and approach used in this study. In

other words, explaining why such homophily and some characteristics foster the formation of ties between neighbourhoods requires other approaches such as qualitative or ethnographic methods (Papachristos and Bastomski, 2018b). Second, the analysis is restricted by the availability and limitations of the open data, thus, only selected neighbourhoods' characteristics were included in this study. Other characteristics that have been shown to foster connections between neighbourhoods (e.g., relationships among street gangs, familial ties, or the distribution of governmental resources) were not included in the models. Third, this study focuses on a specific type of crime (property crime), and the findings and observed patterns should not be generalized to other types of crime without concrete evidence to that effect. Lastly, only one type of tie between neighbourhoods, crime co-movement, was examined. This single type may not represent the full picture, and other ties such as commuting flows and co-offending may be consequential in connecting neighbourhoods and affecting the crime co-movement network.

These limitations highlight that further research should examine the extent to which such patterns hold under different historical and geographic considerations. Including other types of ties (e.g., commuting flows) is also a promising direction for further research, to provide a more comprehensive understanding of crime co-movement.

References

- ANDERS, J. P. 2019. The Long Run Effects of Transformational Federal Policies: Redlining, the Affordable Care Act and Head Start.
- ANSELIN, L., COHEN, J., COOK, D., GORR, W. & TITA, G. 2000. Spatial analyses of crime. *Criminal justice*, 4, 213-262.
- BALLER, R. D., ANSELIN, L., MESSNER, S. F., DEANE, G. & HAWKINS, D. F. 2001. Structural covariates of US county homicide rates: Incorporating spatial effects. *Criminology*, 39, 561-588.
- BANNISTER, J., BATES, E. & KEARNS, A. 2018. Local variance in the crime drop: a longitudinal study of neighbourhoods in greater Glasgow, Scotland. *The British Journal of Criminology*, 58, 177-199.
- BELLAIR, P. E. & BROWNING, C. R. 2010. Contemporary disorganization research: An assessment and further test of the systemic model of neighbourhood crime. *Journal of research in crime and delinquency*, 47, 496-521.
- BILLINGS, S. B., DEMING, D. J. & ROCKOFF, J. 2014. School segregation, educational attainment, and crime: Evidence from the end of busing in Charlotte-Mecklenburg. *The Quarterly Journal of Economics*, 129, 435-476.
- BLUMSTEIN, A. & ROSENFELD, R. 1998. Explaining recent trends in US homicide rates. *The Journal of Criminal Law and Criminology (1973-)*, 88, 1175-1216.
- BRAGA, A. A., PAPACHRISTOS, V. A. & HUREAU, D. M. 2010. The concentration and stability of gun violence at micro places in Boston, 1980–2008. *Journal of Quantitative Criminology*, 26, 33-53.
- BYRNE, J. M. & SAMPSON, R. J. 1986. Key issues in the social ecology of crime. *The social ecology of crime*.
- COHEN, J. & TITA, G. 1999. Diffusion in homicide: Exploring a general method for detecting spatial diffusion processes. *Journal of Quantitative Criminology*, 15, 451-493.
- Contractor, N.S., Wasserman, S. and Faust, K., 2006. Testing multitheoretical, multilevel hypotheses about organizational networks: An analytic framework and empirical example. *Academy of management review*, 31(3), pp.681-703.
- CROWDER, K. & SOUTH, S. J. 2011. Spatial and temporal dimensions of neighbourhood effects on high school graduation. *Social science research*, 40, 87-106.
- DEAN, N., DONG, G., PIEKUT, A. & PRYCE, G. 2019. Frontiers in residential segregation: Understanding neighbourhood boundaries and their impacts. *Tijdschrift voor economische en sociale geografie*, 110, 271-288.
- DEAN, N. & PRYCE, G. 2017. Is the housing market blind to religion? A perceived substitutability approach to homophily and social integration. *Urban Studies*, 54, 3058-3070.
- DIETZ, R. D. & HAURIN, D. R. 2003. The social and private micro-level consequences of homeownership. *Journal of Urban Economics*, 54, 401-450.
- Dollard, J., Miller, N. E., Doob, L. W., Mowrer, O. H., & Sears, R. R. (1939). *Frustration and aggression*. New Haven, CT: Yale University Press

- Džuverović, N., 2013. Does more (or less) lead to violence? Application of the relative deprivation hypothesis on economic inequality-induced conflicts. *Croatian International Relations Review*, 19(68), pp.115-134.
- GRAIF, C., FREELIN, B. N., KUO, Y.-H., WANG, H., LI, Z. & KIFER, D. 2021. Network spillovers and neighbourhood crime: A computational statistics analysis of employment-based networks of neighbourhoods. *Justice Quarterly*, 38, 344-374.
- GRAIF, C., LUNGEANU, A. & YETTER, A. M. 2017. Neighbourhood isolation in Chicago: Violent crime effects on structural isolation and homophily in inter-neighbourhood commuting networks. *Social networks*, 51, 40-59.
- GRAIF, C. & MATTHEWS, S. A. 2017. The long arm of poverty: extended and relational geographies of child victimization and neighbourhood violence exposures. *Justice quarterly*, 34, 1096-1125.
- GROFF, E. R. & LA VIGNE, N. G. 2001. Mapping an opportunity surface of residential burglary. *Journal of Research in Crime and Delinquency*, 38, 257-278.
- GURR, T.R., 1970. Why Men Rebel Princeton University Press. *New Jersey*.
- HANDCOCK, M. S., HUNTER, D. R., BUTTS, C. T., GOODREAU, S. M. & MORRIS, M. 2008. statnet: Software tools for the representation, visualization, analysis and simulation of network data. *Journal of statistical software*, 24, 1548.
- HARCOURT, B. E. & LUDWIG, J. 2006. Broken windows: New evidence from New York City and a five-city social experiment. *U. Chi. L. Rev.*, 73, 271.
- Harris, J.K., 2013. *An introduction to exponential random graph modeling* (Vol. 173). Sage Publications.
- HEITGERD, J. L. & BURSİK JR, R. J. 1987. Extracommunity dynamics and the ecology of delinquency. *American Journal of Sociology*, 92, 775-787.
- HIPP, J. R. 2007. Income inequality, race, and place: Does the distribution of race and class within neighbourhoods affect crime rates? *Criminology*, 45, 665-697.
- HIRSCHFIELD, A., BIRKIN, M., BRUNSDON, C., MALLESON, N. & NEWTON, A. 2014. How Places Influence Crime: The Impact of Surrounding Areas on Neighbourhood Burglary Rates in a British City. *Urban Studies*, 51, 1057-1072.
- Hunter, D.R., Handcock, M.S., Butts, C.T., Goodreau, S.M. and Morris, M., 2008. ergm: A package to fit, simulate and diagnose exponential-family models for networks. *Journal of statistical software*, 24(3).
- Kawachi, I., Kennedy, B.P. and Wilkinson, R.G., 1999. Crime: social disorganization and relative deprivation. *Social science & medicine*, 48(6), pp.719-731.
- KIRK, D. S. 2009. A natural experiment on residential change and recidivism: Lessons from Hurricane Katrina. *American Sociological Review*, 74, 484-505.
- KRIVO, L. J. & PETERSON, R. D. 1996. Extremely disadvantaged neighbourhoods and urban crime. *Social forces*, 75, 619-648.
- LA VIGNE, N. G. 2003. A portrait of prisoner reentry in Illinois.

- MCPHERSON, M., SMITH-LOVIN, L. & COOK, J. M. 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology*, 27, 415-444.
- Legewie, J. (2018). Living on the edge: neighbourhoodneighborhood boundaries and the spatial dynamics of violent crime. *Demography*, 55(5), 1957-1977.
- Legewie, J., & Schaeffer, M. (2016). Contested boundaries: Explaining where ethnoracial diversity provokes neighbourhoodneighborhood conflict. *American Journal of Sociology*, 122(1), 125-161.
- MEARS, D. P. & BHATI, A. S. 2006. No community is an island: The effects of resource deprivation on urban violence in spatially and socially proximate communities. *Criminology*, 44, 509-548.
- MORENOFF, J. D. & SAMPSON, R. J. 1997. Violent crime and the spatial dynamics of neighbourhood transition: Chicago, 1970–1990. *Social forces*, 76, 31-64.
- MORENOFF, J. D., SAMPSON, R. J. & RAUDENBUSH, S. W. 2001. Neighbourhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, 39, 517-558.
- MURPHY, A. K. & WALLACE, D. 2010. Opportunities for making ends meet and upward mobility: Differences in organizational deprivation across urban and suburban poor neighbourhoods. *Social Science Quarterly*, 91, 1164-1186.
- PAPACHRISTOS, V. A. & BASTOMSKI, S. 2018. Connected in crime: The enduring effect of neighbourhood networks on the spatial patterning of violence. *American Journal of Sociology*, 124, 517-568.
- PARK, R. E. & BURGESS, E. W. 1925. *The City: Suggestions for Investigation of Human Behavior in the Urban Environmen.*, University of Chicago Press.
- PETERSON, R. D. & KRIVO, L. J. 2009. Segregated spatial locations, race-ethnic composition, and neighbourhood violent crime. *The Annals of the American Academy of Political and Social Science*, 623, 93-107.
- PETERSON, R. D., KRIVO, L. J. & HAGAN, J. 2010. *Divergent social worlds: Neighbourhood crime and the racial-spatial divide*, Criminal Justice Research Center, Ohio State University, United States.
- Iyer, Aarti & Pryce, Gwilym. 2022. theorising the Causal Impacts of Social Frontiers: The Social and Psychological Implications of Discontinuities in the Geography of Residential Mix. (Working Paper).
- SAMPSON, R. J. 2004. Networks and neighbourhoods. *Demos Collection*, 155-166.
- SAMPSON, R. J. 2012. *Great American city: Chicago and the enduring neighbourhood effect*.
- SAMPSON, R. J. & GROVES, W. B. 1989. Community structure and crime: Testing social-disorganization theory. *American journal of sociology*, 94, 774-802.
- SAMPSON, R. J., RAUDENBUSH, S. W. & EARLS, F. 1997. Neighbourhoods and violent crime: A multilevel study of collective efficacy. *Science*, 277, 918-924.
- SCHAEFER, D. R. 2012. Youth co-offending networks: An investigation of social and spatial effects. *Social Networks*, 34, 141-149.
- SCHUERMAN, L. & KOBRIN, S. 1986. Community careers in crime. *Crime and justice*, 8, 67-100.
- SHAW, C. R. & MCKAY, H. D. 1942. Juvenile delinquency and urban areas.
- SMALL, M. L. & MCDERMOTT, M. 2006. The presence of organizational resources in poor urban neighbourhoods: An analysis of average and contextual effects. *Social Forces*, 84, 1697-1724.

- TITA, G. E. & GREENBAUM, R. T. 2009. Crime, neighbourhoods, and units of analysis: putting space in its place. *Putting crime in its place*.
- TRAN, V. C., GRAIF, C., JONES, A. D., SMALL, M. L. & WINSHIP, C. 2013. Participation in context: Neighbourhood diversity and organizational involvement in Boston. *City & Community*, 12, 187-210.
- VOGEL, M. & SOUTH, S. J. 2016. Spatial dimensions of the effect of neighbourhood disadvantage on delinquency. *Criminology*, 54, 434-458.
- Wasserman, S. and Pattison, P., 1996. Logit models and logistic regressions for social networks: I. An introduction to Markov graphs andp. *Psychometrika*, 61(3), pp.401-425.
- WEISBURD, D., BUSHWAY, S., LUM, C. & YANG, S. M. 2004. Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology*, 42, 283-322.
- WEISBURD, D., GROFF, E. R. & YANG, S.-M. 2012. *The criminology of place: Street segments and our understanding of the crime problem*.
- WEISBURD, D., MAHER, L., SHERMAN, L., BUERGER, M., COHN, E. & PETRISINO, A. 1992. Contrasting crime general and crime specific theory: The case of hot spots of crime. *Advances in criminological theory*, 4, 45-69.
- WELLMAN, B. 1999. The network community: An introduction. *Networks in the global village: Life in contemporary communities*, 1-47.
- ZEOLI, A. M., PIZARRO, J. M., GRADY, S. C. & MELDE, C. 2014. Homicide as infectious disease: Using public health methods to investigate the diffusion of homicide. *Justice quarterly*, 31, 609-632.

CHAPTER 5

Spatial Networks of Neighbourhood Violence

5.1 Introduction

In the previous chapter, I introduced the notion of crime co-movement networks as a way of thinking about the structural relations between neighbourhood crime rates. These networks reveal the nature of interdependencies in ways that incorporate spatial connections but are not limited to them, and allow us to explore the idea of assortative mixing (or homophily) in crime dynamics. We have considered the idea of hidden vulnerabilities common causing neighbourhoods to have similar crime responses to external shocks, thus resulting in their crime trajectories moving in tandem. However, as well as having common vulnerabilities and socio-economic features, neighbourhoods with close co-movements in crime rates may also be linked by underlying social networks which give rise to, and are reinforced by, strong population flows between them.

In this chapter, I therefore build on the network structures approach by exploring the role of population flows in determining interdependencies in neighbourhood violence, focusing in particular on co-movements of shooting incidents in the city of Chicago. I draw on previous research examining the relationship between neighbourhood networks and crime in order to answer two research questions: (1) What is the impact of people's movement flows on the co-movement of shooting incidents across Chicago's neighbourhoods? (2) To what extent does homophily and spatial proximity explain the co-movement of shooting incidents across Chicago's neighbourhoods? To my knowledge, no previous research has tested these questions, largely owing to data limitations. The main novel contribution of the present study lies in its examination of both

people's movement flows across neighbourhoods and homophily—each of which is treated, herein, as a possible underlying mechanism shaping the co-movement of violence across neighbourhoods.

I approached this research by analysing the co-movement of shooting incidents over the six-year period between 2014 and 2020 in the major US city of Chicago, located in the Midwestern state of Illinois. Using shooting-incident data, a mobile phone origin–destination (MPOD) dataset, and US census data, I estimated a set of exponential random graph models (ERGMs) to investigate the attributes of neighbourhoods that foster shooting co-movement. The analysis shows that two factors—high movement flows between neighbourhoods and socio-economic similarity between neighbourhoods—increases the likelihood that co-movement will exist in shootings, irrespective of spatial proximity between neighbourhoods.

The remainder of this chapter is structured as follows. To provide some background, in section 4.2, I review the literature on violence diffusion, distribution, networks and population flows. In section 4.3, I set out the conceptual framework underpinning the study, followed by a description of the data and methods in section 4.4. The results are presented in section 4.5 and discussed in section 4.6.

5.2 Background

5.2.1 Violence diffusion

The nature of violence in the United States has undergone massive changes in the past sixty years. The national violence rate began rising in the 1960s and continued through the early 1990s before peaking in 1993. In that year, there were 17,075 homicides (Blumstein, 1995; Cook and Laub, 1998). Thereafter, the United States experienced a dramatic decrease in violence, with gun

homicides down 40% by the end of 2000. This decline continued through the 2010s ending in 2014. Since then, violence has surged dramatically, reaching its highest levels in the years since 1990s (Sharkey and Marsteller, 2022). As a case in point, 2016 marked the most violent year for Chicago in the previous twenty years, with the city experiencing almost two murders per day (Mueller and Baker, 2017, Larsen et al., 2017).

A considerable number of empirical studies have investigated violent crime (e.g., Cohen and Tita, 1999, Morenoff et al., 2001, Tita and Cohen, 2004, Ratcliffe and Rengert, 2008, Braga et al., 2010b) at various geographic levels such as the county level (e.g., Messner et al., 1999), the census tract level (e.g., Tita and Cohen, 2004), and the block level (e.g., Ratcliffe and Rengert, 2008). The upshot of all these studies is that violence in America has had notable regional concentrations and exhibited spatiotemporal non-random clustering.

The ways in which violence is diffused throughout society has long been a question of great interest to scholars. Some of them have suggested that an individual's social network can serve as an underlying channel for violence propagation (Papachristos et al., 2015). Violence in general, and shooting incidents in particular, have also been described as retaliatory incidents; that is, shooting incidents are often connected to earlier violent crimes. The contagion perspective provides a theoretical foundation for understanding both the diffusion of violence and appropriate policy interventions. Some contagion theories have examined the timescales and mechanisms in which violence exhibits a cascading nature (Loeffler and Flaxman, 2018). In their work on contagion theory, Blumstein (1995) and Flannery et al. (2007) found an association between changes in illegal markets and subsequent growth in gun violence.

Given the recent surge in gun violence afflicting many US cities (Braga et al., 2010a, Sharkey and Marsteller, 2022) and the retaliatory nature of gun shootings within disadvantaged

social networks (Morenoff et al., 2001, Tita and Ridgeway, 2007, Papachristos, 2009), empirical research has been investigating whether or not the dynamics of these shootings could be a key to interventions aiming to reduce violence. Recent research has recognised the importance of studying the relationship between violence and social networks and has uncovered evidence that violence is embedded in social networks (Blumstein and Rosenfeld, 1998, Papachristos, 2009, Papachristos et al., 2015, Short et al., 2014, Green et al., 2017). However, a closer examination of the literature on violent-crime diffusion reveals that relatively little attention has been paid to the dynamics and the co-movement of shooting incidents on the scale of neighbourhoods.

The uneven distribution of violence in America has been the focus of crime research since Shaw and McKay (1942). Together, they studied delinquency rates across Chicago's neighbourhoods and found that deprivation, residential mobility, and ethnic heterogeneity were associated with elevated rates of violence. After the ground-breaking research of Shaw and McKay (1942), researchers studied factors that had been associated with spikes in neighbourhood violence. To date, the most robust findings in the violence literature are, first, that violence is concentrated in some—not all—neighbourhoods and that this concentration is observable even in micro-geographic units such as street corners (Sherman et al., 1989, Braga et al., 2010a, Weisburd et al., 2012) and, second, that particular neighbourhood characteristics such as underdevelopment (Kondo et al., 2018, Harding, 2010, Sharkey and Marsteller, 2022), concentrated poverty (Sampson et al., 1997), racial segregation and disinvestment in communities (Sharkey, 2014) can predict high levels of violence. These findings are unlikely to be particularly surprising. Indeed, the highly uneven distribution of violence across Chicago's neighbourhoods has been evident for all to see: homicide rates in African American communities are twenty times higher than in proximate predominantly white communities (Papachristos and Bastomski, 2018a).

In the past few years, studies examining crime diffusion have highlighted the important interdependent link between neighbourhoods and crime, especially with regard to spatial dependencies. Recent research has provided evidence that crime diffusion can surpass neighbourhood boundaries (Anselin et al., 2000, Anselin, 2002, Graif et al., 2021, Morenoff et al., 2001) and that crime rates are mirrored in proximate neighbourhoods (Peterson and Krivo, 2009, Tita and Greenbaum, 2009). For example, using homicide data over a twenty-year period in Newark, New Jersey, Zeoli et al. (2014) found evidence of a stable spatiotemporal diffusion process, where rising rates of homicides started in the city centre (i.e., Newark's "downtown") and disseminated southward and westward during the study period.

Such findings lead naturally to the question of why violence spreads out in certain directions but not others, besetting some neighbourhoods while leaving others mostly unscathed. Are the neighbourhood-level trajectories of violence uniform, and if not, what might cause them to vary? Neighbourhoods have been conceptualized as urban villages, with distinct social and spatial characteristics (Papachristos and Bastomski, 2018a). Regardless of spatial proximity, neighbourhoods can be connected to one another by common values or separated by factors such as poverty and racial segregation — the city acting as a "mosaic of little worlds which touch but do not interpenetrate" (Park and Burgess, 1925, p. 40). In the words of (Mears and Bhati, 2006), "Communities do not exist in isolation...they may affect and be affected by other communities with which they coexist and interact". Despite having recognized the importance of understanding the non-random patterns of crime diffusion, research has yet to empirically investigate the precise mechanisms driving these patterns across neighbourhoods.

Recently, therefore, research has emerged that moves beyond a focus on intra-neighbourhood settings and that recognizes the importance of connections between

neighbourhoods. “Neighbourhoods are themselves nodes in a larger network of spatial relations” (Sampson, 2004). Conceptually, scholars have argued that social proximity, as well as spatial proximity, can promote criminogenic ties and the diffusion of crime. Social ties are sometimes “spatially unbounded”; that is, individuals can be socially connected with residents of distant areas through various channels (Wellman, 1999b, Mears and Bhati, 2006). Crime-related connections between neighbourhoods, irrespective of the spatial proximity between them, are predicted by two major factors: (1) criminal behaviour such as co-offending (Schaefer, 2012, Papachristos and Bastomski, 2018a) and participation in illicit drug markets (Cork, 1999, Sampson, 2012, Tita and Boessen, 2011); and (2) non-criminal behaviour such as commuting (Graif et al., 2021) and homophily, or the general propensity to associate with like people (Papachristos and Bastomski, 2018a).

Furthermore, the mobility and interconnectedness of urban life require individuals to spend a lot of time on activities that occur outside their residential spaces—a fact that increases their exposure to other neighbourhoods (Sampson and Levy, 2020, Graif et al., 2021). Thus, recent studies have recognised that self-contained residential neighbourhoods are not the be all end all contributors to crime rates. Recent research has linked intra-community settings with mechanisms that promote co-offending (Schaefer, 2012, Papachristos and Bastomski, 2018a), gang conflicts (Papachristos et al., 2013), residential instability (Sampson and Sharkey, 2008), and commuting to work (Graif et al., 2021). However, previous research in neighbourhood networks has not examined how mechanisms such as people movement flows affect the co-movement of crime. Graif et al. (2021) examined both workplace commuting and exposure to workplaces in disadvantaged neighbourhoods, but did not include in their examination either the mobility factor of individuals or the role of inter-neighbourhood movement in violence rates.

Studies that focus on violence diffusion across neighbourhoods suffer from two major weaknesses. First, much of the research has used typical statistical methods that model aggregated crime rates in predictable ways and that overlook important social interactions capable of mirroring and inducing social phenomena, regardless of whether they are characterised by stability or change (Papachristos and Bastomski, 2018a). Second, existing research that has investigated the dynamics of inter-community crime relies heavily on various forms of regression analysis. However, these statistical models are less than ideal for estimating the degree of dependence between neighbourhoods because these models rest on the assumption that neighbourhoods are independent of one another or only dependent in a very limited way (e.g. through spatial lags). Research has shown that neighbourhood crime rates are affected by crime, delinquency, and victimization rates in proximate neighbourhoods, indicating spatial proximity effect on crime dynamics (Crowder and South, 2011, Morenoff et al., 2001, Peterson and Krivo, 2010, Vogel and South, 2016). Spatial econometric methods relax this assumption of independence but only in a very specific and limited way; for instance, they might allow for dependence between neighbourhoods that are contiguous or in close proximity. Distant neighbourhoods, however, are assumed to be unconnected. If we want to understand how a range of factors—not just distance or contiguity—might affect the co-movement of violence across time and space, we need to employ methods that allow for any two neighbourhoods to be potentially connected. This means using network analysis to study inter-neighbourhood dependencies in crime. However, to my knowledge, network-oriented methods have yet to be applied in the literature examining the co-movement of violence.

5.2.2 Violence Distribution

The geographic concentration and non-random distribution of violent crime have been an enduring feature of American cities (Anselin et al., 2000, Sampson et al., 2002). In their pioneering

work, (Shaw and McKay, 1942) provided empirical evidence of this association by analysing a thirty-year period of Chicago's crime rates. They found that crime rates were driven by certain neighbourhood characteristics, provided evidence specifically that neighbourhood delinquency rates are a function of social issues. Following Shaw and McKay (1942), a great amount of literature has studied how neighbourhood conditions predict crime, and some of the research has found that concentrated disadvantage and socioeconomic conditions are strong predictors of violence (Peterson and Krivo, 1993, Morenoff et al., 2001, Weisburd et al., 2012). Since Shaw and McKay (1942), much of the literature has sought to identify and clarify the factors that contribute to local crime. Previous research has provided evidence that local crime rates are associated with several types of neighbourhood-based socioeconomic disadvantage, including poverty, unemployment, inequality, and segregation.

One of the most robust findings in the violence literature is that violence is concentrated in specific neighbourhoods and in a small fraction of micro-geographic units, including the previously mentioned example of street corners (Sherman et al., 1989, Braga et al., 2010a, Weisburd et al., 2012). The concentrated nature of this violence may account for major changes in citywide crime rates throughout the United States. Weisburd et al. (2004) examined 1.4 million crime reports from the northwestern city of Seattle, adopting a street-block level analysis spanning the period between 1989 and 2002. Their analysis revealed that Seattle was the site of a high geographical concentration of crime over time, with between approximately 4% and 5% of street blocks accounting for 50% of overall crime. In an extension of their previous research, Weisburd et al. (2009) examined a 13-year period of juvenile arrest incidents in Seattle. Again, the results confirmed that a concentration of incidents existed: between 3% and 5% of the street blocks

accounted for almost all instances of arrest. Moreover, Weisburd et al. (2012) found that fewer than 5% of street blocks accounted for 50% of crimes.

This persistent concentration of crime is mirrored in both the clustering of social problems and the presence of particular neighbourhood characteristics including declining conditions in local housing development, concentrated poverty and racial segregation, and disinvestment in communities, which independently and collectively have predicted high levels of violence (Sharkey and Marsteller, 2022, Harding, 2010, Sampson et al., 1997).

Sharkey and Marsteller (2022) argued that this concentration of crime is a function of inequalities across neighbourhoods. Supporting this view, Peterson and Krivo (2010) studied neighbourhoods in 91 cities across the United States and found a significant association between inequality and violence rates. On average, the violence rates in predominantly black neighbourhoods were 327% higher than in predominantly white neighbourhoods; similarly, only 20% of the black neighbourhoods had low violence levels, whereas 90% of the white neighbourhoods did. A few years later, Sharkey (2014) presented research findings on the structural inequalities in census tracts across the United States: quite notably, 87% of predominantly black neighbourhoods and 83% of predominantly Hispanic neighbourhoods suffered from significant socioeconomic disadvantage and were, in many cases, surrounded by disadvantaged neighbourhoods. In contrast, only 15% of the predominantly white neighbourhoods suffered from local or proximate disadvantage.

The above-cited research shows that social problems such as inequality and disadvantage appear to profoundly affect the distribution of populations across neighbourhoods, in turn helping explain why crime rates are higher in some neighbourhoods than in others. However, many neighbourhoods are neither socially nor spatially disconnected from one another; they are nodes

in a large network (Sampson, 2004), and they simultaneously affect and are affected by the conditions of proximate neighbourhoods. Growing awareness of the interdependence of neighbourhoods has prompted researchers to consider moving beyond the traditional focus on intra-neighbourhood dynamics (Peterson and Krivo, 2009, Tita and Greenbaum, 2009). According to several studies on the interconnected nature of neighbourhoods, (1) violence rates spread spatially in ways that transcend neighbourhood boundaries and (2) the socioeconomic conditions of proximate neighbourhoods are a strong predictor of local violence in given neighbourhoods (Anselin et al., 2000, Morenoff et al., 2001, Kirk, 2009, Sampson, 2012).

5.2.3 Neighbourhoods' Networks and Crime

How does crime spread across neighbourhoods? Quite a few empirical studies have tried to answer this question by studying the mechanisms that link neighbourhoods to one another and that determine the structure of crime diffusion. During the last twenty years, research has provided evidence that crime diffusion surpasses neighbourhood boundaries (Anselin et al., 2000, Anselin, 2002, Graif et al., 2014, Morenoff et al., 2001, Peterson and Krivo, 2010). For example, poring over homicide data that covered a twenty-year period in Newark, New Jersey, Zeoli et al. (2014) found evidence of a stable spatiotemporal diffusion process, where rising rates of homicides were emerging in the city centre at the start of the twenty-year period and then disseminated southward and westward during the subsequent two decades. The impact of spatial proximity is a robust finding in the crime-diffusion research at various levels of geographic aggregation.

When we consider the mechanisms that drive the diffusion of crime, a question arises regarding the extent to which the diffusion occurs because of spatial proximity rather than because of other characteristics such as social proximity. Conceptually, scholars have argued that not only does spatial proximity promote criminogenic ties and the diffusion of crime, but social proximity

does so, as well. Social ties are “spatially unbounded”; that is, individuals—through several channels—can be socially connected with others from geographically distant areas (Wellman, 1999a, Mears and Bhati, 2006). Recent empirical studies support this perspective. Schaefer (2012) studied co-offending networks in Maricopa County, Arizona, and uncovered evidence that social proximity contributes to the structure of criminogenic networks. More specifically, he found that neighbourhoods with similar demographic characteristics are more likely to be connected and to share co-offending ties than are demographically disparate neighbourhoods. Similarly, a recent study by Papachristos and Bastomski (2018b) examined how criminal co-offending forges connections between various neighbourhoods in Chicago. The results confirm that spatial proximity is important for the phenomenon of linked neighbourhoods. The results also confirm that co-offending ties were common between socially similar neighbourhoods, irrespective of the distance between them. Finally, Mears and Bhati (2006) studied violence diffusion across Chicago neighbourhoods and found that local neighbourhood deprivation is a strong predictor of violence in socially proximate communities.

5.2.4 Movement Flows

Urban lifestyles and the nature of interconnected societies promote social interactions and increase both the exposure and the movement of individuals to other neighbourhoods. Recent studies have recognised the important role that the flows in “people’s movement” can play in crime rates across neighbourhoods. A prized area of research in the field of sociology concerns the many types of connections that bind people to one another and that range from social ties and familial relations to workplace attachments (Marsden and Hurlbert, 1988). Resources and institutions including education institutes, childcare centres, and city parks bring together people from various residential areas and, thus, increase the flows in people’s movement across neighbourhoods (Small

and McDermott, 2006, Murphy and Wallace, 2010, Tran et al., 2013). Also, both public transportation and commercial commuting influence the daily flows and the routine activities of various groups of people (Graif et al., 2021). A handful of studies have examined the impact that commuting flows can have on patterns of crime diffusion. For instance, studying data from a twelve-year period across Chicago neighbourhoods, Graif et al. (2017) focused on how work-commuting flows influence the rates of neighbourhood violent crime. They found that higher rates were associated with fewer inter-neighbourhood ties. Additionally, the researchers found evidence of homophilous commuting ties between neighbourhoods—leading to the conclusion that similarity in neighbourhood-violence rates increases the likelihood that commuting ties will form. Similarly, Graif et al. (2019) found that local crime rates were associated with the inter-neighbourhood commuting networks to disadvantage communities.

Regarding patterns of disconnectedness, Sampson and Levy (2020) studied racial residential segregation and mobility-based disconnectedness in an effort to clarify the extent to which racial segregation led to mobility-based disconnectedness and to reduced mobility in common hubs of visitation. They found that not only is residential segregation linked to higher rates of violent crime, but it also results in less commuting between communities and fewer trips to central locations. In addition, rates of violence are strongly linked to the concentrated mobility.

5.3 Conceptual Framework

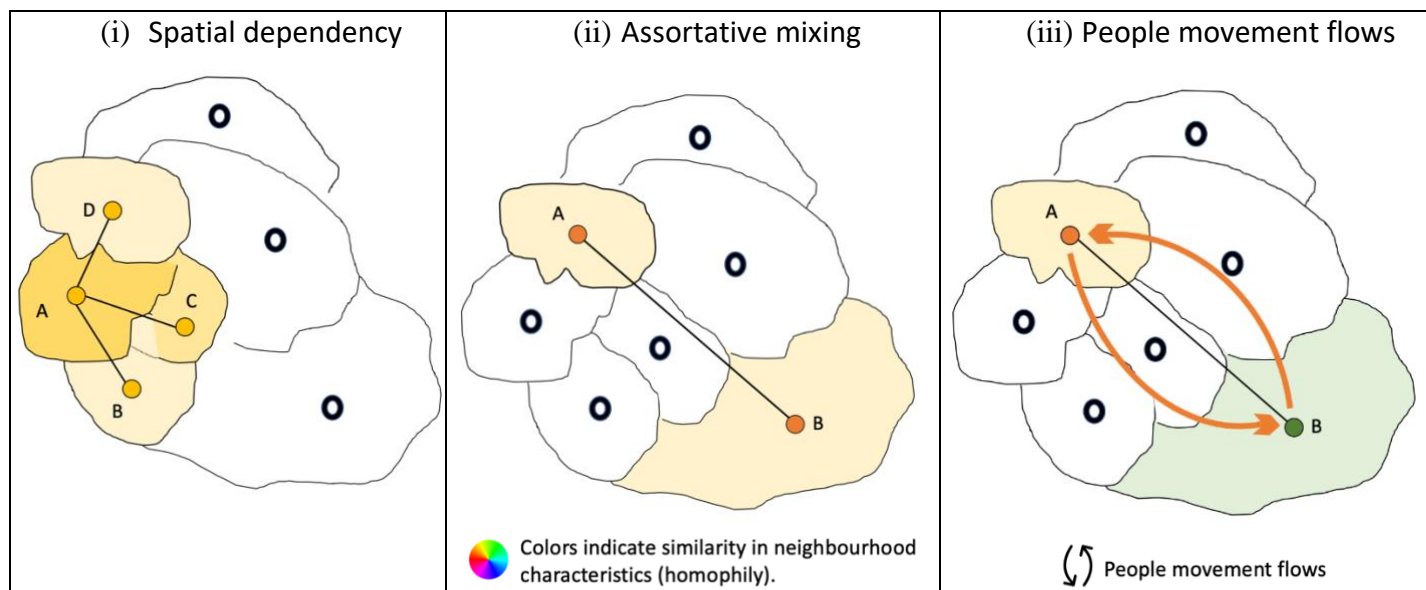


Figure 18 Conceptual framework

Two important themes emerge from the literature discussed above. First, neighbourhoods are not isolated islands, but are connected to each other through various mechanisms such as those related to co-offending, work commuting, and gang conflicts. Second, both urban mobility and social interconnectedness increase the exposure of individuals to other areas. The existing research on neighbourhood networks has examined a host of mechanisms that connect neighbourhoods to one another and that affect citywide commuting patterns. Nevertheless, how a mobility-based network affects the dynamics of violence over time is unknown. Although previous studies have provided evidence about the impact of certain type of commuting flows (e.g., work commuting) on local crime rates, no studies have conceptualized the co-movement of violence rates as a type of network to explore the potential mechanisms driving violence dynamics across neighbourhoods. In this chapter, I conceptualise the co-movement of shooting incidents as a type of network. I am interested in the mechanisms generating similarity in temporal dynamics of violence. The core question is whether neighbourhoods move together because: firstly, they are part of the same

community (i.e. distance is a proxy for similar dynamics) as represented in Figure 9 panel (i); secondly, they have similar population characteristics (i.e. homophily) as represented in Figure 9 panel (ii), and/or thirdly, they are linking people together through direct interactions (i.e. movement flows) as represented in Figure 9 panel (iii). Therefore, traditional statistical methods such as regression models are inappropriate for the present study because they assume that, in the data, each unit of observation (i.e., each neighbourhood) is independent from all others. This conditional independence assumption is clearly problematic, as it precludes the very phenomenon I am seeking to study.

For the present study, I created a model of networked violence dynamics, in which ties between neighbourhoods occur if their shooting incidents move in tandem. Then I explored the extent to which three important factors—(1) spatial proximity, (2) similarity between neighbourhoods and (3) individuals' movement flows—predict inter-neighbourhood ties. I next explored the extent to which inter-neighbourhood dependency can occur, especially in cases involving neighbourhoods that are not in close geographical proximity to one another.

(1) *Spatial proximity*. The form of dependence is shown graphically in the map of stylised neighbourhood depicted in Figure 18 panel (i), where the dots represent neighbourhood centroids which can also be thought of as nodes in a network, and the links between nodes represent co-movement of crime rates between a pair of neighbourhoods. The idea of spatial dependence shown by the links between neighbourhood A and its contiguous neighbours, B, C and D. Alternatively, the spatial dependence might be defined in terms of geographical distance with the closest neighbourhoods having the strongest levels of co-dependence in terms of crime trajectories. The theoretical rationale for this approach is Tobler's First Law of Geography: everything is related to everything else, but near things are more related than distant things" (Tobler 1970). This has been

borne out in the crime distribution literature which has shown that contiguity/spatial proximity is a crucial factor in explaining crime distribution. Crime rates in one neighbourhood are influenced by crime rates in surrounding neighbourhoods (e.g., Morenoff et al., 2001, Zeoli et al., 2014). In particular, previous studies indicating that disadvantage in geographically proximate neighbourhoods affects—or at least is very significantly associated with—crime rates and victimization in proximate neighbourhoods (Morenoff et al., 2001, Peterson and Krivo, 2009, Peterson et al., 2010, Crowder and South, 2011, Vogel and South, 2016). These findings are also in line with a previous study showing that crime rates may be affected by poverty in proximate neighbourhoods (Graif and Matthews, 2017). Thus, we should expect crime co-movement links are more likely to be formed between proximate neighbourhoods.

(2) *Social proximity (homophily)*. In the social-network literature, the widely observed tendency for individuals to form ties with similar individuals rather than with dissimilar individuals is described as “assortative mixing” or “homophily.” As for the types of similarities involved herein, they can be defined by culture, race, gender, social background, similar life experiences, and similar socioeconomic resources. McPherson et al. (2001) described homophily as “the principle that a contact between similar people occurs at a higher rate than among dissimilar people” (p. 416). Hence, homophily asserts that the more similar a pair of people are to each other, the more likely they will be to connect with each other. Thus, if neighbourhood crime dynamics are subject to the influence of homophily, the following principle may hold: the more similar a pair of neighbourhoods are to each other, the more likely they will be to connect with each other in many observable ways, including the co-movement of shootings incidents. In other words, homophily means that nodes are more likely to be connected if they are similar. As shown in Figure 18 panel (ii), neighbourhoods A and B are similar in some important characteristic such as poverty

rates, and are therefore likely to be connected in terms of co-movements of shooting incidents, but they are not geographically contiguous. The same nodes' colour indicates a similarity between neighbourhood A and B in terms of their attributes (e.g., demographic, socioeconomic, etc). Thus, if neighbourhood A and B are said to be homophilous, it means that neighbourhoods A and B are more likely to be connected in terms of co-movement of crime if they have similar attributes.

Hence, if the shooting incidents ties that are explored in this study are more likely to occur between neighbourhoods having similar attributes than between quite distinctly attributed neighbourhoods, I would conclude that my study offers considerable evidence of homophily in violence dynamics.

(3) *Movement flows*. Understanding the relationship between people movement flows across neighbourhood and the co-movement of violence is important for several reasons. First, higher movement flows among people travelling between two neighbourhoods are associated with increases in the potential of inter-neighbourhood social-tie formation (Sampson and Levy, 2020). A previous study in Chicago by Sampson (2012) provided evidence that social ties affect residential choices, because people seeking a home tend to move to a neighbourhood where they had prior social connections. Furthermore, prior research found that such social ties (1) require social interactions across neighbourhoods, a phenomenon that relies on the movement of information between neighbourhoods (Sampson and Levy, 2020) and (2) increase the likelihood of co-offending networks (Papachristos and Bastomski, 2018a, Schaefer, 2012). Second, this movement of people can shape the movement of information, attitudes, cultural practices, and beliefs across neighbourhoods, resulting in changes that are mirrored in the city as a whole (Sampson and Levy, 2020). By conceptualizing the city as a network of neighbourhoods, researchers can better understand the dynamics of violence and, in particular, how social issues

(e.g., racial segregation, concentrated poverty) affect individuals' mobility and, in turn, may help to understand the co-movement of violence. As shown in Figure 18 panel (iii), neighbourhoods A and B are not contiguous, but experienced higher people movement flows between them and therefore are likely to be connected in terms of co-movements of shooting incidents. The arrows indicate movement flows between neighbourhood A and B. Thus, the higher the movement flows between neighbourhood A and B, the more likely neighbourhoods A and B are to be connected in terms of co-movement of crime.

5.4 Methods

5.4.1 Study Location

This study uses data on the city of Chicago, the largest city in the state of Illinois and the third most populous city in the United States with over 2.7 million residents. Chicago has been known for its high rate of violence for many decades and “used to making the national news for violence.” The city features racial, ethnic, and income segregation (Sharkey and Marsteller, 2022) and was labelled the “murder capital” of the United States (Huq and Rappaport, 2022). Thus, since Shaw and McKay (1942), Chicago has been the study area for many groundbreaking theories such as community social processes and violence (Sampson, 2012), and the transformation of urban poverty (Wilson, 1987). Thus, Chicago was selected to build on the decades of research conducted in Chicago. According to the Census Bureau (2020), the racial composition of Chicago was as follows: Black or African American: 28%, white: 33%, Hispanic or Latino: 28%, and other races: 11%.

5.4.2 Crime Data

I obtained this study's shooting-incident data from the American Violence Project, a violence-data centre located at New York University (americanviolence.org)⁴. The data cover the annual shooting incidents in each census tract in Chicago for the period between 2014 and 2020. A census tract is an area established by the US Census Bureau as roughly equal to a neighbourhood, the population of which typically ranges between 1,200 and 8,000 residents. Census tracts have been used to represent neighbourhoods in many ecological studies of crime (e.g., Krivo and Peterson, 1996, Morenoff and Sampson, 1997, Peterson et al., 2000). For the city of Chicago, there are 833 census tracts, 731 of which were included in the present study (with the remainder excluded owing to their insufficient data).

5.4.3 Neighbourhoods' Networks

For the purposes of this study, I have examined neighbourhood networks in relation to the co-movement of shooting incidents during the designated study period. Neighbourhoods A and B are said to be linked to each other if their patterns of shooting incidents follow similar trajectories. As examined herein, neighbourhood networks therefore consist of nodes (neighbourhoods) and the edges that link one node to another. These nodes (neighbourhoods) are said to be linked to each other if there is a high correlation over time between the dynamics of their respective shooting incidents.

Let $G(V,E)$ be an undirected network, where V is the set of neighbourhoods in the city and E is the set of edges. The links between neighbourhoods can be summarized with an adjacency matrix, C , the elements of which represent the pairwise shooting trajectory correlation between

⁴ <https://marroninstitute.nyu.edu/blog>

node i and node j . An edge between two nodes i and j exists if the crime rates of these two neighbourhoods follow similar trajectory, or “move together” (i.e., exhibit co-movement). The measure of shooting incident co-movement is denoted by correlation C_{ij} , so that an edge is said to exist between i and j if C_{ij} is greater than N , where N is the threshold for the correlation of shooting incident trajectories. The threshold selection rests on the stability of model results (i.e., the stability of variable coefficients). Hence, the threshold selection began from a base threshold of 0.50, with the value of correlation incrementally increased until the results stability was found. The model results show that stability was achieved in the 0.50–0.90 range, and the threshold of 0.90 was selected.

5.4.4 Exponential random graph models (ERGMs)

The Exponential family is a family of statistical models for many types of data and the Exponential random graph models (ERGMs) is a statistical model for analysing social network. In social network analysis, there are several metrics and measurements exist to describe the structure of an observed network like density, betweenness, centrality, etc. These metrics, however, characterise the observed network, which is just one of many possible alternative networks. The structural properties of this group of alternative networks may be similar or dissimilar. In other words, the observed network is thought to be one of many possible networks formed by an unknown stochastic process that models potential network links as a random variable (Wasserman and Pattison 1996). Thus, the aim of an ERGM is to examine the factors that influence tie formation between nodes. Thus, ERGM provide a model for statistical inference for network structure and the processes influencing the existence (and absence) of network ties. The model takes the network as a graph constituted by nodes and edges (ties) between nodes and examine the factors that influence ties formation between nodes. Thus, due to the relational nature of network

data, ERGM violates the assumptions of independence of standard statistical models such as linear regression. 9,10. Such models assume that each unit of observation in the data (in this case, neighbourhoods) is independent from all others. The conditional independence assumption is clearly problematic if we are interested in what determines the inter-neighbourhood dependence of crime dynamics as it precludes the very phenomenon we are seeking to study. ERGMs are theory driven so researchers need to consider the complex theoretical reasons for the emergence of social links in the observed network.

The basic ERGM takes the form:

$$pr(X = x) = \left(\frac{1}{k}\right) exp \left\{ \sum_A \eta_A g_A(x) \right\}$$

The model specifies the probability of a set of ties, X , for all possible nodes with node features, dyad attributes, and observed network statistics (Lusher et al., 2013; Robins et al., 2007). g_A is a vector of network statistics, η_A is a vector of corresponding coefficients, and A indexes multiple statistics in $g(x)$. The variable k is a normalizing constant for the distribution. Ergm packages in R were used for all models (Hunter et al., 2008).

5.4.5 Variables

I obtained several measures of neighbourhood characteristics from US census data (2014). (1) poverty rate, which designates the percentage of families whose incomes are below the poverty line; (2) black population, which designates the percentage of residents who are Black/African American; (3) Hispanic population, which designates the percentage of residents who are Hispanic; (4) residential instability, which is reflected in the percentage of households that moved

to the given neighbourhood after 2010 and the percentage of housing that is renter-occupied (I standardized each of the indicators, summed the resulting z-scores, and then divided these sums by the number of indicators in order to construct each scale); (5) youth population: which designates the population aged 10–17. (6) older people which designates the population aged 55+. (7) spatial proximity, which refers to the geographic distance, measured in miles, between neighbourhood centroids; and (8) people-mobility flows obtained from SafeGraph (SafeGraph.com)⁵, which are calculated on the basis of millions of anonymous mobile phone users' visit trajectories to various places⁶.

Table 7 Census tract descriptive statistics (N = 731)

	Median	Mean	St. Dev.
Poverty	19.30	21.46	14.87
Black	13.77	39.50	41.14
Hispanic	12.95	27.21	30.13
Resident instability	59.40	56.74	20.09
Youth population	14.40	14.92	6.85
Older population	20.40	21.12	8.35
Total population	3177	3463	1800

⁵ From SafeGraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places, via the SafeGraph Community. To enhance privacy, SafeGraph excludes census block group information if fewer than two devices visited an establishment in a month from a given census block group.

⁶ The mobility data was computed, aggregated, and inferred the daily dynamic origin-to-destination (O-D) population flows at the census-tract level, and then trimmed the flows down to pairs consisting of at least 10 daily trips on average. The data were aggregated for 2019, which served as the annual base.

5.4.6 Strategy

I estimated a series of ERGMs in order to identify which factors cause two neighbourhoods to be linked to each other. In other words, I sought by this method to explore the impact of homophily and movement flows on the formation of co-movement ties related to shooting incidents. The method specifically required that I examine the impact of movement flows, social distance, and spatial proximity. The movement flows constructed by calculating the number of visits between each pair of census tracts in 2019. Social distance is the extent of dissimilarity between neighbourhoods in terms of poverty level, the black segment of the population, the Hispanic segment of the population, residential instability, and age composition. Social distance was measured by calculating the absolute differences between the neighbourhood characteristics for all possible dyads in the network. As for spatial proximity, it is defined as spatial distance, which I constructed by calculating the number of miles between neighbourhood centroids.

The exponential graph models were estimated as follows. The first model was estimated as a control model for examining how a neighbourhood's features were associated with crime co-movement ties to other neighbourhoods, but not for examining the effects of movement flows, social distance, or spatial distance (i.e., not for examining the homophily). Next, to examine the effects of spatial and social distances and the contributions of these distances to the first model, I added the social characteristics of neighbourhoods and the geographic distances between them to the second model. With the third model, I examined the effects of movement flows. Finally, AIC was used to assess the improvement in models to determine the contribution of each dimension to explain the network structure of the network.

5.5 Results

Table 8 presents the ERGM results regarding the impact of social and spatial distance, and movement flows on the formation of shooting-incident co-movement ties between neighbourhoods. The first model in the series of ERGMs is the baseline model. It includes the neighbourhood characteristics that were expected to impact the formation of shooting-incident co-movement ties. For each neighbourhood, Model 1 includes node covariates for poverty level, the black segment of the population, the Hispanic segment of the population, residential instability, and age composition. As shown in Table 1, neighbourhoods whose populations had a high proportion of blacks or Hispanics were less likely to display crime co-movement ties than were neighbourhoods in which those demographic groups accounted for a small percentage of the population. By contrast, the higher the proportion of youths in a neighbourhood's population, the higher the probability of crime co-movement ties in the neighbourhood. In Model 1, the edges term is negative, which is normal in ERGMs and shows that, overall, ties were less likely to exist than not exist in this network.

Model 2 covers several edge covariates that, by strengthening the examination of social distance and the geographic distance between neighbourhoods, helped me evaluate how homophily influences the formation of ties. The influence of homophily was calculated as the absolute difference between each pair of neighbourhoods with respect to the levels of poverty in each neighbourhood, the percentage of blacks and Hispanics in each neighbourhood, the residential instability of each neighbourhood, and the age composition of each neighbourhood. As shown in Table 8, these three measures of social distance were significantly and negatively associated with the formation of ties between neighbourhoods—the greater the differences, the weaker the probability of ties existence. The fact that the associations were negative indicates that,

in general, social dissimilarity between neighbourhoods reduces the probability of there being ties between the neighbourhoods; in other words, the more similar a pair of neighbourhoods are to each other (at least in terms of some social characteristics), the more likely the neighbourhoods are to be linked to each other. Regarding this study's data, strong similarity in poverty levels and in the percentages of blacks and youths was strongly associated with high levels of shooting ties between neighbourhoods. Thus, neighbourhoods with similar levels of poverty and similar percentages of blacks and youths were more likely to experience similar shooting-incident trajectories. By contrast, differences between two neighbourhoods regarding the percentage of seniors in the given population had a significant positive association with tie formation; that is, the greater the difference, the stronger the ties. Put yet another way, neighbourhoods with similar levels of seniors in the population were less likely to be connected to each other than were neighbourhoods with contrasting levels of seniors. Also worth noting is the significant negative association between geographic distance and neighbourhood ties: greater distance between neighbourhoods reduces the likelihood their crime co-movement ties. In sum, Model 2 yielded better AIC results than did Model 1 (i.e., the baseline model), indicating that Model 2 fits the data better than Model 1.

Model 3 evaluates the association between people's movement flows from one neighbourhood to another and shooting ties between these neighbourhoods. The association was found to be significantly positive, indicating that the movement flows between neighbourhoods constituted an important factor in the formation of shooting ties. Put succinctly, the greater the movement flows were between neighbourhoods, the more likely the neighbourhoods were to exhibit co-movement ties with regard to shooting incidents. The AIC for Model 3 turned out to be lower than the AIC scores for the previous two models, indicating that Model 3 is the most reasonable of the three models considered thus far.

Model 4 covers social distances, spatial distances, and movement flows but only for non-contiguous neighbourhoods. The purpose of this model was to determine whether or not the results of the previous models were driven largely or even exclusively by the close proximity of neighbourhoods. The results of Model 4 are consistent with the results of the first three models with respect to the black demographic factor and the two age-group demographic factors. However, in Model 4, the poverty and spatial-distance factors were no longer significantly associated with the formation of inter-neighbourhood ties.

Taken together, the results of the four models yield the following key insights. First, socio-demographic similarity and people's movement flows were, in all the models, robust factors associated with the co-movement of shooting incidents between neighbourhoods. Second, spatial proximity helps to explain why neighbourhoods shooting incidents move together, and part of the explanation is driven by flows of movement. This becomes clearer when remove ties to adjacent tracts removed in model 4; that shows that proximity still matters, but much less so - and flows of movement are still a core part of why proximity matters. Hence, neighbourhoods move together in part because they have similar composition, and in part because of the movement flows of people tie neighbourhoods together. Third, the model with the best fit (i.e., Model 3) comprised all the measures, indicating that spatial proximity, homophily, and movement flows are key determinants in Chicago's shooting-incident co-movement networks.

Table 8 Coefficients and standard errors from exponential random graph models

	Model1	model 2	model 3	Model 4
	B (SE)	B (SE)	B (SE)	B (SE)
edges	-4.52*** (0.01)	-4.14*** (0.06)	-4.23*** (0.06)	-4.33*** (0.07)
Neighbourhood characteristics:				
% Poverty	0.01 (0.02)	0.04 (0.02)	0.04 (0.03)	0.03 (0.02)
% Black	-0.16*** (0.03)	-0.17*** (0.03)	-0.16* (0.03)	-0.17*** (0.03)
% Hispanic	-0.14*** (0.01)	-0.19*** (0.02)	-0.18*** (0.02)	-0.18*** (0.02)
Residential Instability	0.05** (0.02)	0.03 (0.01)	0.03 (0.02)	0.03* (0.01)
% Age 15-24	0.06*** (0.01)	0.10*** (0.01)	0.11*** (0.01)	0.10*** (0.01)
% Age 55 and over	0.04* (0.01)	0.03* (0.02)	0.03* (0.02)	0.03 (0.02)
Social_distance: (homophily test)				
% Poverty		-0.05* (0.03)	-0.05 (0.03)	-0.04 (0.02)
% Black		-0.08** (0.02)	-0.08** (0.03)	-0.09** (0.03)
% Hispanic		0.04 (0.02)	0.04 (0.03)	0.04 (0.03)
Residential Instability		-0.02 (0.02)	-0.02 (0.02)	-0.03 (0.02)
% Age 15-24		-0.10*** (0.02)	-0.10*** (0.02)	-0.10*** (0.02)
% Age 55 and over		0.05* (0.02)	0.05** (0.02)	0.06** (0.02)
Spatial distance				
Geographic distance		-0.11*** (0.02)	-0.08** (0.03)	-0.03 (0.03)
Movement flows			0.02*** (0.03)	0.02** (0.01)
AIC	30904	30834	30822	30543

5.6 Conclusion

There is a great amount of criminology research that has addressed both the concentration and the distribution of violence, especially in urban settings. In this regard, previous empirical studies have emphasized three robust findings: first, spatial clustering is associated with violent crime; second, violence is non-randomly distributed across neighbourhoods; and third, violent crime spills over into nearby neighbourhoods. Previous empirical studies examined the neighbourhood characteristics that were thought to entail higher violence rates in multiple neighbourhoods in a given city. However, beyond the factor of geographical proximity, little has been revealed about the specific mechanisms responsible for these similarities. By using network theory as my conceptual framework for thinking about the co-movement of violence across neighbourhoods, I have been able to frame the current study's analysis in a way that makes its research questions amenable to statistical network methods. The current study is, as far as I am aware, the first to explicitly investigate the factors driving shooting-incident dynamics between neighbourhoods using network analysis. This approach has two key advantages: (1) it provides a more coherent and comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in violent crime; and (2) it provides a more appropriate empirical framework for analysis that is not constrained by the prohibitive assumptions of node independence assumed in traditional regression analysis.

Thus, I have sought to extend the literature by focusing on co-movement networks involving violence and, more importantly, by exploring these networks' underlying mechanisms, which I have divided into three categories: social proximity, spatial proximity, and people's movement flows, which may promote similarities in shooting trajectories across neighbourhoods. The findings of this research emphasize the key role of spatial distance in the co-movement of

shooting incidents across neighbourhoods. However, spatial distance alone is insufficient to explain the dynamics of violence that characterize cities such as Chicago. Moreover, other factors such as social proximity (homophily) and people's movement flows seem to contribute to the formation of shooting-incident co-movement networks.

Given the many studies of violence that have reported evidence that violence in one neighbourhood spills over into nearby neighbourhoods, it is worth considering why previous research on crime dynamics has not examined other mechanisms that might tie together non-contiguous neighbourhoods in a particular city. One possible explanation is that the previous research has relied heavily on various forms of regression analysis. Regression models are commonly used statistical methods, but because they assume that neighbourhoods are independent from all others, these models would likely fail to capture both inter-neighbourhood dependency and factors potentially capable of linking a city's neighbourhoods to one another. This conditional independence assumption is clearly problematic as it precludes the very phenomenon examined in the present study. Thus, using a more appropriate method such as network analysis can greatly strengthen the possibility that research will shed light on the phenomenon of inter-neighbourhood dependency. Lending support for such analyses are recent examinations of co-offending networks (Schaefer, 2012, Papachristos and Bastomski, 2018a), which show that, in the world of crime, social proximity is a key factor connecting a city's neighbourhoods to one another by creating an extended environment in which criminals co-offend even outside their neighbourhood.

In the present study, I have uncovered evidence that people's movement flows across neighbourhoods significantly influence the co-movement of shooting incidents. That is, the larger a movement flow is between neighbourhoods, the more likely it will be that shooting-incident ties will take shape across the neighbourhoods. This finding must be interpreted with caution, as there

are several possible explanations for the phenomenon. For instance, commercial land use and other resources influence individuals' daily movements across an urban landscape. The lack of resources in disadvantaged areas affects residents' interactions with one another and residents' exposure to other areas, thus entailing the spread of criminal behaviour to other neighbourhoods. Another plausible explanation for the phenomenon is that high-risk places such as illegal-drug markets and liquor stores could stoke aggression and promote criminal behaviours in people who frequent these sites but who live in another neighbourhood. This explanation is consistent with Peterson et al. (2000), which found that bars in local and contiguous neighbourhoods are associated with elevated rates of violent crime in neighbourhoods. Likewise, Groff and Lockwood (2014) reported that bars and subway stops were positively associated with violent crime and property crime in both local and distant areas within a city's limits. Another possibility is that the positive association between movement flows and the co-movement of violent crime is a function of criminals' commuting between each other's residential neighbourhoods. People's tendency to practice homophily at the individual level increases the likelihood that criminals residing in spatially different—but demographically similar—neighbourhoods will establish various positive relationships with one another, thereby promoting criminal activity that a non-resident of a neighbourhood carries out in that neighbourhood.

The present study's findings also show that homophily affects the socioeconomics between neighbourhoods in ways that increase the probability of shooting ties. In particular, similarity in poverty levels and in the black and youth segments of a population seem to significantly increase the likelihood that shooting-incident ties will form between neighbourhoods. These findings are consistent with mechanisms that previous research discussed in relation to co-offending networks. For instance, similarity in socioeconomic characteristics was found to increase the likelihood of

criminal connections between neighbourhoods (Schaefer, 2012, Papachristos and Bastomski, 2018a). A possible explanation for these results is the retaliatory nature of gun shootings among adversarial social networks that span multiple disadvantaged neighbourhoods (Morenoff et al., 2001, Tita and Ridgeway, 2007, Papachristos, 2009). Of course, both racial segregation (Morenoff et al., 2001) and poverty (Sharkey and Marsteller, 2022) exist in many Chicago neighbourhoods, and racial segregation in particular is strongly associated with the incidence of crime: Peterson and Krivo (2010) observed just such an association between inequality and violence rates in, where violence rates in predominantly black neighbourhoods were 327% higher than in predominantly white neighbourhoods. Sharkey (2014) found that socioeconomic disadvantage was concentrated in 87% of the black neighbourhoods. In contrast, only 15% of the white neighbourhoods suffered from local or proximate disadvantage. Also, in a recent study, Sampson and Levy (2020) provided suggestive evidence for the impact of such disadvantaged connectedness on the homicide and violence rate in Chicago.

Finally, the additional analysis that eliminate ties to bordering neighbourhoods show a persistent positive impact of the movement flows on the shooting dynamics. The current study shows that people's movement flows were persistently and positively associated with the dynamics of shooting incidents. This finding is evidence that close spatial proximity between neighbourhoods is not the sole cause of shooting co-movement network. These findings provide evidence that the violent crime dynamics are not simply driven by people in close proximity. That is, spatial proximity alone is insufficient to explain the dynamics of violence across neighbourhoods dynamics. The present study lends credence to the argument that other factors contribute to the formation of criminal-violence co-movement networks.

Taken together, these findings suggest a role for spatial proximity in explaining why neighbourhoods shooting incidents move together; and part of the explanation is driven by flows of movement. This becomes clearer when remove ties to adjacent tracts removed; that shows that proximity still matters, but much less so - and flows of movement are still a core part of why proximity matters. Hence, neighbourhoods move together in part because they have similar composition, and in part because of the movement flows of people tie neighbourhoods together.

This research has limitations. First, whilst the findings provide evidence associating both movement flows and homophily with the formation of violence co-movement ties among neighbourhoods, it is difficult to precisely explain the nature and the extent of these associations, largely because both the data and the methods used in this study have their own limitations. Other methodological approaches such as qualitative or ethnographic methods can perhaps better explain why both movement flows and homophily seem to foster the formation of criminal ties between neighbourhoods (Papachristos and Bastomski, 2018b). Second, my analysis of people's movement flows was restricted by the limited availability and extent of the data. Thus, I included in this study only the 2019 daily trips. Future work that incorporates a shorter timeframe of both shooting incident trajectories and movement flows might be a very valuable resource for understanding and even predicting violent crime. Third, this study focuses on a specific type of crime (i.e., shooting incidents), and all things being equal, the findings and observed patterns cannot be rigorously generalized to other types of crimes. Lastly, for this study, I examined only one type of tie between neighbourhoods, crime co-movement, yet neighbourhoods connect with each other in many other ways, including the forging of relationships among street gangs, the lasting influence of familial ties, and the distribution of governmental resources. Thus, further experimental investigations

would do well to explore the influences that a wide range of factors may have on the dynamics of shooting incidents in urban settings.

A number of implications have emerged from this research. At the methodological level, my effort to conceptualize the violence co-movement as a network of neighbourhoods sheds light on some very poorly understood phenomena, which include the dynamics of violence and the effects of spatial proximity, homophily, and movement flows on the co-movement of violence. By conceiving of violence dynamics as a type of network, I have helped to overcome weaknesses in commonly used statistical methods and have strengthened the possibility that researchers and practitioners in the field can reasonably understand mechanisms that drive the co-movement of violence. At a policy level, the connectedness of neighbourhoods indicates that crime-prevention strategies and policies may lose some of their effectiveness if neighbourhoods are treated in isolation from one another. That is, a focus on the violence levels in one neighbourhood may be insufficient to reduce its rates of violence if connected but overlooked neighbourhoods are playing a major role in the violence. Policy that focuses as much on neighbourhood networks as on individual neighbourhoods may reveal important factors that would otherwise remain hidden and that can help reduce crime rates citywide (Graif et al., 2021).

Reference

- ANSELIN, L. 2002. Mapping and analysis for spatial social science. *Center for Spatially Integrated Social Science, University of California, Santa Barbara, CA.*
- ANSELIN, L., COHEN, J., COOK, D., GORR, W. & TITA, G. 2000. Spatial analyses of crime. *Criminal justice*, 4, 213-262.
- BLUMSTEIN, A. 1995. Youth violence, guns, and the illicit-drug industry. *J. Crim. L. & Criminology*, 86, 10.
- BLUMSTEIN, A. & ROSENFELD, R. 1998. Explaining recent trends in US homicide rates. *The Journal of Criminal Law and Criminology (1973-)*, 88, 1175-1216.
- BRAGA, A. A., PAPACHRISTOS, A. V. & HUREAU, D. M. 2010a. The concentration and stability of gun violence at micro places in Boston, 1980–2008. *Journal of Quantitative Criminology*, 26, 33-53.
- BRAGA, A. A., PAPACHRISTOS, V. A. & HUREAU, D. M. 2010b. The concentration and stability of gun violence at micro places in Boston, 1980–2008. *Journal of Quantitative Criminology*, 26, 33-53.
- COHEN, J. & TITA, G. 1999. Diffusion in homicide: Exploring a general method for detecting spatial diffusion processes. *Journal of Quantitative Criminology*, 15, 451-493.
- COOK, P. J. & LAUB, J. H. 1998. The unprecedented epidemic in youth violence. *Crime and justice*, 24, 27-64.
- CORK, D. 1999. Examining space–time interaction in city-level homicide data: crack markets and the diffusion of guns among youth. *Journal of Quantitative Criminology*, 15, 379-406.
- CROWDER, K. & SOUTH, S. J. 2011. Spatial and temporal dimensions of neighbourhood effects on high school graduation. *Social science research*, 40, 87-106.
- DEAN, N. & PRYCE, G. 2017. Is the housing market blind to religion? A perceived substitutability approach to homophily and social integration. *Urban Studies*, 54, 3058-3070.
- FLANNERY, D. J., VAZSONYI, A. T. & WALDMAN, I. D. 2007. *The Cambridge handbook of violent behavior and aggression*, Cambridge University Press.
- GRAIF, C., FREELIN, B. N., KUO, Y.-H., WANG, H., LI, Z. & KIFER, D. 2021. Network spillovers and neighbourhood crime: A computational statistics analysis of employment-based networks of neighbourhoods. *Justice Quarterly*, 38, 344-374.
- GRAIF, C., GLADFELTER, A. S. & MATTHEWS, S. A. 2014. Urban poverty and neighbourhood effects on crime: Incorporating spatial and network perspectives. *Sociology compass*, 8, 1140-1155.
- GRAIF, C., LUNGEANU, A. & YETTER, A. M. 2017. Neighbourhood isolation in Chicago: Violent crime effects on structural isolation and homophily in inter-neighbourhood commuting networks. *Social networks*, 51, 40-59.
- GREEN, B., HOREL, T. & PAPACHRISTOS, A. V. 2017. Modeling contagion through social networks to explain and predict gunshot violence in Chicago, 2006 to 2014. *JAMA internal medicine*, 177, 326-333.
- GROFF, E. R. & LOCKWOOD, B. 2014. Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *Journal of Research in Crime and Delinquency*, 51, 277-314.

- HARDING, D. J. 2010. *Living the drama: Community, conflict, and culture among inner-city boys*, University of Chicago Press.
- HUQ, A. Z. & RAPPAPORT, J. 2022. Symposium Introduction: This Violent City? Urban Violence in Chicago and Beyond. *The University of Chicago Law Review*, 89, 303-321.
- KIRK, D. S. 2009. A natural experiment on residential change and recidivism: Lessons from Hurricane Katrina. *American Sociological Review*, 74, 484-505.
- KONDO, M. C., ANDREYEVA, E., SOUTH, E. C., MACDONALD, J. M. & BRANAS, C. C. 2018. Neighbourhood interventions to reduce violence. *Annual review of public health*, 39, 253-271.
- KRIVO, L. J. & PETERSON, R. D. 1996. Extremely disadvantaged neighbourhoods and urban crime. *Social forces*, 75, 619-648.
- LARSEN, D. A., LANE, S., JENNINGS-BEY, T., HAYGOOD-EL, A., BRUNDAGE, K. & RUBINSTEIN, R. A. 2017. Spatio-temporal patterns of gun violence in Syracuse, New York 2009-2015. *PLoS One*, 12, e0173001.
- LOEFFLER, C. & FLAXMAN, S. 2018. Is gun violence contagious? A spatiotemporal test. *Journal of quantitative criminology*, 34, 999-1017.
- MARSDEN, P. V. & HURLBERT, J. S. 1988. Social resources and mobility outcomes: A replication and extension. *Social forces*, 66, 1038-1059.
- MCPHERSON, M., SMITH-LOVIN, L. & COOK, J. M. 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology*, 27, 415-444.
- MEARS, D. P. & BHATI, A. S. 2006. No community is an island: The effects of resource deprivation on urban violence in spatially and socially proximate communities. *Criminology*, 44, 509-548.
- MESSNER, S. F., ANSELIN, L., BALLER, R. D., HAWKINS, D. F., DEANE, G. & TOLNAY, S. E. 1999. The spatial patterning of county homicide rates: An application of exploratory spatial data analysis. *Journal of Quantitative criminology*, 15, 423-450.
- MORENOFF, J. D. & SAMPSON, R. J. 1997. Violent crime and the spatial dynamics of neighbourhood transition: Chicago, 1970–1990. *Social forces*, 76, 31-64.
- MORENOFF, J. D., SAMPSON, R. J. & RAUDENBUSH, S. W. 2001. Neighbourhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, 39, 517-558.
- MUELLER, B. & BAKER, A. 2017. Drop in gang violence drove New York City shootings below 1,000 in 2016. *New York Times. New York City*, 3.
- MURPHY, A. K. & WALLACE, D. 2010. Opportunities for making ends meet and upward mobility: Differences in organizational deprivation across urban and suburban poor neighbourhoods. *Social Science Quarterly*, 91, 1164-1186.
- PAPACHRISTOS, A. V. 2009. Murder by structure: Dominance relations and the social structure of gang homicide. *American journal of sociology*, 115, 74-128.
- PAPACHRISTOS, A. V. & BASTOMSKI, S. 2018a. Connected in crime: The enduring effect of neighbourhood networks on the spatial patterning of violence. *American Journal of Sociology*, 124, 517-568.

- PAPACHRISTOS, A. V., BRAGA, A. A., PIZA, E. & GROSSMAN, L. S. 2015. The company you keep? The spillover effects of gang membership on individual gunshot victimization in a co-offending network. *Criminology*, 53, 624-649.
- PAPACHRISTOS, A. V., HUREAU, D. M. & BRAGA, A. A. 2013. The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence. *American Sociological Review*, 78, 417-447.
- PAPACHRISTOS, V. A. & BASTOMSKI, S. 2018b. Connected in crime: The enduring effect of neighbourhood networks on the spatial patterning of violence. *American Journal of Sociology*, 124, 517-568.
- PARK, R. E. & BURGESS, E. W. 1925. *The City: Suggestions for Investigation of Human Behavior in the Urban Environmen.*, University of Chicago Press.
- PETERSON, R. D. & KRIVO, L. J. 1993. Racial segregation and black urban homicide. *Social Forces*, 71, 1001-1026.
- PETERSON, R. D. & KRIVO, L. J. 2009. Segregated spatial locations, race-ethnic composition, and neighbourhood violent crime. *The Annals of the American Academy of Political and Social Science*, 623, 93-107.
- PETERSON, R. D. & KRIVO, L. J. 2010. *Divergent social worlds: Neighbourhood crime and the racial-spatial divide*, Russell Sage Foundation.
- PETERSON, R. D., KRIVO, L. J. & HARRIS, M. A. 2000. Disadvantage and neighbourhood violent crime: Do local institutions matter? *Journal of research in crime and delinquency*, 37, 31-63.
- RATCLIFFE, J. H. & RENGERT, G. F. 2008. Near-repeat patterns in Philadelphia shootings. *Security Journal*, 21, 58-76.
- SAMPSON, R. J. 2004. Networks and neighbourhoods. *Demos Collection*, 155-166.
- SAMPSON, R. J. 2012. *Great American city: Chicago and the enduring neighbourhood effect*.
- SAMPSON, R. J. & LEVY, B. L. 2020. Beyond residential segregation: mobility-based connectedness and rates of violence in large cities. *Race and social problems*, 12, 77-86.
- SAMPSON, R. J., MORENOFF, J. D. & GANNON-ROWLEY, T. 2002. Assessing “neighbourhood effects”: Social processes and new directions in research. *Annual review of sociology*, 28, 443-478.
- SAMPSON, R. J., RAUDENBUSH, S. W. & EARLS, F. 1997. Neighbourhoods and violent crime: A multilevel study of collective efficacy. *Science*, 277, 918-924.
- SAMPSON, R. J. & SHARKEY, P. 2008. Neighbourhood selection and the social reproduction of concentrated racial inequality. *Demography*, 45, 1-29.
- SCHAEFER, D. R. 2012. Youth co-offending networks: An investigation of social and spatial effects. *Social Networks*, 34, 141-149.
- SHARKEY, P. 2014. Spatial segmentation and the black middle class. *American Journal of Sociology*, 119, 903-954.
- SHARKEY, P. & MARSTELLER, A. 2022. Neighbourhood Inequality and Violence in Chicago, 1965–2020. *U. CHI. L. REV.*, 89, 349, 351.
- SHAW, C. R. & MCKAY, H. D. 1942. Juvenile delinquency and urban areas.
- SHERMAN, L. W., GARTIN, P. R. & BUERGER, M. E. 1989. Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, 27, 27-56.

- SHORT, M. B., MOHLER, G. O., BRANTINGHAM, P. J. & TITA, G. E. 2014. Gang rivalry dynamics via coupled point process networks. *Discrete & Continuous Dynamical Systems-B*, 19, 1459.
- SMALL, M. L. & MCDERMOTT, M. 2006. The presence of organizational resources in poor urban neighbourhoods: An analysis of average and contextual effects. *Social Forces*, 84, 1697-1724.
- TITA, G. & COHEN, J. 2004. Measuring spatial diffusion of shots fired activity across city neighbourhoods. *Spatially integrated social science*, 171-204.
- TITA, G. & RIDGEWAY, G. 2007. The impact of gang formation on local patterns of crime. *Journal of Research in Crime and Delinquency*, 44, 208-237.
- TITA, G. E. & BOESSEN, A. 2011. Social networks and the ecology of crime: using social network data to understand the spatial distribution of crime. *The SAGE handbook of criminological research methods*, 128-142.
- TITA, G. E. & GREENBAUM, R. T. 2009. Crime, neighbourhoods, and units of analysis: putting space in its place. *Putting crime in its place*.
- TRAN, V. C., GRAIF, C., JONES, A. D., SMALL, M. L. & WINSHIP, C. 2013. Participation in context: Neighbourhood diversity and organizational involvement in Boston. *City & Community*, 12, 187-210.
- VOGEL, M. & SOUTH, S. J. 2016. Spatial dimensions of the effect of neighbourhood disadvantage on delinquency. *Criminology*, 54, 434-458.
- WEISBURD, D., BUSHWAY, S., LUM, C. & YANG, S. M. 2004. Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology*, 42, 283-322.
- WEISBURD, D., GROFF, E. R. & YANG, S.-M. 2012. *The criminology of place: Street segments and our understanding of the crime problem*.
- WEISBURD, D., MORRIS, N. A. & GROFF, E. R. 2009. Hot spots of juvenile crime: A longitudinal study of arrest incidents at street segments in Seattle, Washington. *Journal of quantitative criminology*, 25, 443-467.
- WELLMAN, B. 1999a. The network community: An introduction. *Networks in the global village: Life in contemporary communities*, 1-47.
- WELLMAN, B. 1999b. *Networks in the Global Village Boulder. CO: Westview*.
- WILSON, W. J. 1987. The Truly Disadvantaged: The Inner City. *The Underclass, and Public Policy*, 8.
- ZEOLI, A. M., PIZARRO, J. M., GRADY, S. C. & MELDE, C. 2014. Homicide as infectious disease: Using public health methods to investigate the diffusion of homicide. *Justice quarterly*, 31, 609-632.

CHAPTER 6

Conclusion

For many decades, extensive research has been conducted on the problem of crime. One topic of special interest to researchers and practitioners alike has been neighbourhood crime trajectories. However, very little light has been shed on this topic with respect to neighbourhood interdependencies that arise from factors other than geographical proximity. Prior research has emphasized the spatial clustering of crime and the similarity and stability of crime trajectories over time in spatial units such as street segments and neighbourhoods. Despite these research efforts, the mechanisms driving neighbourhoods' crime co-movement have not been explored with statistical methods that can accommodate the full range of potential dependencies between observational units. This is because the literature has relied on traditional methods which assumes that observational units are independent, or permits dependence in very specific ways, such as spatial contiguity or proximity. The aim of this thesis was to gain an understanding of neighbourhoods' interdependencies and to explore the potential underlying factors that are associated with the co-movement of neighbourhoods' crime trajectories. To address these aims, two types of analysis have been employed: trajectory clustering in chapter 3 and social network analysis in chapters 4 and 5. I started the exploration by clustering the neighbourhoods by their crime trajectories. Specifically, I used the k-means clustering method to identify groups of neighbourhoods experiencing similar crime trajectories over time. Then, to understand the potential factors that are associated with the co-movement of neighbourhoods' crime trajectories, I used multinomial logistic regression to test whether there were systematic drivers of trajectory

group membership. Whilst clustering neighbourhoods on the basis of similarity of crime trajectories – as in chapter 3 – these clusters remain a ‘black box’ in the sense that much of the underlying structures of interdependence remain hidden. Spatial econometric approaches (Anselin et al., 2000) are of some value in identifying dependencies defined in terms of spatial proximity or contiguity, but they overlook non-spatial dependencies arising from "assortative mixing" in non-spatial attributes or account for them in a very specific and limited way. This limitation motivated me to look at the problem from a different angle and come up with a novel way to investigate the crime co-movement phenomenon. Therefore, in chapters 4 and 5, I conceptualised the co-movement of crime trajectories as a type of network and then explored the mechanisms generating similarity in the temporal dynamics of crime. In order to understand the potential underlying factors that are associated with the co-movement of, I focused on a core question that was whether neighbourhoods move together because they are part of the same community (i.e., distance is a proxy for similar dynamics), they have similar population characteristics (i.e., homophily), and/or they are linking people together through direct interactions (i.e., movement flows). In order to examine the impact of homophily, a number of neighbourhood characteristics were included in the analysis, such as poverty, unemployment, age compositions, racial compositions, family disruption, historical discrimination.

By using network theory as the conceptual framework for the co-movement of crime across neighbourhoods, I have been able to frame the analysis in a way that makes the linkages between neighbourhoods the primary focus and that provides a conceptual framework for thinking about the structure of inter-neighbourhood connections and what this means for how we understand crime. The approach also makes my research questions amenable to statistical network methods which offer a more appropriate set of empirical tools than traditional regression analysis. Mine is,

to the best of my knowledge, the first study that explicitly investigates a broad range of factors driving the co-movement of crime between neighbourhoods and that does so with appropriate research methods. Conceptualizing the co-movement of crime as a type of network helped to overcome prior method limitations that have been employed to study such an issue in three different ways. First, social network analysis overcomes the limitation of clustering analysis, which only allows for exploring group-level connections. Thus, using social network analysis, I was able to explore the underlying structures of interdependence and was able to explore the pairwise connections between neighbourhoods or analyse the factors that drive them. Second, unlike the spatial econometric approaches, social network analysis and exponential graph models were more appropriate methods to identify the pairwise dependencies defined in terms of spatial proximity or contiguity, and non-spatial dependencies arising from "assortative mixing" in non-spatial attributes. Third, it strengthens the possibility to create reasonably comprehensive portraits of neighbourhood crime co-movement and provide insights into the attributes and possible causal factors linking similar neighbourhoods to one another.

The findings of this thesis reveal several key insights. First, the impact of spatial-proximity was robust in all analyses, indicating that spatial proximity was significantly associated with the co-movement of crime trajectories between neighbourhoods. This confirms the idea of the spatial dependence impact that was defined and discussed in chapter 1. The spatial dependence was defined in terms of geographical distance, with the proximate neighbourhoods having stronger levels of co-dependence in terms of crime trajectories. This is also consistent with the theoretical rationale for this approach, which is Tobler's First Law of Geography that suggests that everything is related to everything else, but near things are more related than distant things" (Tobler, 1970).

This finding is also in line with a previous study showing that crime rates may be affected by characteristics in proximate neighbourhoods (Graif and Matthews, 2017).

To understand why spatial proximity is unlikely to be the only source of dependency between neighbourhood crime rates, I have sought to expand the underlying conceptual framework used to think about inter-neighbourhood dependencies by exploring non-spatial dependence (homophily). The social network literature, the widely observed tendency for individuals to form ties with similar individuals (versus dissimilar individuals) is described as "assortative mixing" or "homophily". The similarity can be defined by culture, race, gender, social background, similar life experiences and socioeconomic resources. Hence, I built on the social network literature by exploring impact of homophily on neighbourhood crime dynamics networks. Thus, if neighbourhood crime dynamics are subject to the influence of homophily, the following principle may hold: the more similar a pair of neighbourhoods are to each other, the more likely they will be to connect with each other in many observable ways, including the co-movement of shootings incidents. In other words, homophily means that nodes are more likely to be connected if they are similar. The findings confirmed the impact of homophily in socioeconomics between Chicago's neighbourhoods in ways that increase the probability of shooting ties. In particular, similarity in poverty levels and in the black population seem to significantly increase the likelihood that shooting-incident ties will form between neighbourhoods. These findings are consistent with mechanisms that previous research discussed in relation to co-offending networks. For instance, similarity in socioeconomic characteristics was found to increase the likelihood of criminal connections between neighbourhoods (Schaefer, 2012; Papachristos and Bastomski, 2018a).

While the underlying conceptual driver of the discussed mechanisms above is the similarity between neighbourhoods, there are reasons to believe that in some situations the opposite may be

true. Contrasting neighbourhoods in close proximity may be more likely to experience inter-group conflict and this may cause a malignant connection to emerge between two adjacent neighbourhoods that drives co-movements in crime. That is crime rates in contiguous neighbourhoods are more likely to move in tandem when those neighbourhoods have sharply contrasting levels of disadvantage. Interestingly, the findings showed that the heterogeneity in the level of disadvantage increases the likelihood of the property crime co-movement ties between contiguous neighbourhoods in Cleveland. That is, ties are more likely to exist between neighbourhoods with a dissimilar level of disadvantage, indicating patterns of heterophily in tie formation. The additional model that controlled for contiguity and measure the effect of the social frontier confirmed the heterophily effect; indicating that these links are more likely to exist due to the effects of social frontier. This accords with Iyer and Pryce (2022) that argued that marked relative deprivation between contiguous neighbourhoods could give rise to a type of "social frontier" which heightens territorial behaviour and inter-group conflict. As a result, we may see the opposite of a homophily effect where contiguous neighbourhoods with marked differences in affluence have similar crime dynamics due to this conflict. However, to my knowledge, this effect has yet to be studied empirically within the more capacious framework of network analysis. Relative deprivation theory (RDT) provides a potentially useful theoretical framework to understand the conflict that can arise from proximate inequality (Džuverovic, 2013). According to RDT, a person or group's subjective dissatisfaction is caused by their relative position to another person or group's situation or position (Gurr, 1970). Relative deprivation is therefore present when a person or group lacks the resources to maintain the standard of living, activities, and luxuries to which they are accustomed, or which are generally supported by the society to which they belong (Runciman, 1966). Due to the social pressure, individuals' tendency to continually compare their

own situation with the situation or position of the rest of society increases if this is not attainable. Accordingly, contrasting neighbourhoods in other dimensions of residential mix may also be linked through social tensions, rivalry and territoriality. The relative deprivation literature (e.g., Džuverovic, 2013, Dollard et al. 1939, Kawachi et al., 1999) has long argued that inequalities in wealth and income can be a source of social tension and crime.

More recently, researchers (e.g., Graif and Matthews, 2017) have speculated that population movements between neighbourhoods can provide another source of potential connection between neighbourhood crime rates. Again, however, these effects have not been considered within a network context to study the co-movement of crime, and so have not taken into account the full range of potential connections between neighbourhood crime rates when modelling the effect. Understanding the relationship between people movement flows across neighbourhood and the co-movement of violence is important for several reasons. First, higher movement flows among people travelling between two neighbourhoods are associated with increases in the potential for inter-neighbourhood social-tie formation (Sampson and Levy, 2020). Second, this movement of people can shape the movement of information, attitudes, cultural practices, and beliefs across neighbourhoods, resulting in changes that are mirrored in the city as a whole (Sampson and Levy, 2020).

The findings uncovered evidence that people's movement flows across Chicago's neighbourhoods significantly influence the co-movement of shooting incidents. That is, the larger a movement flow is between neighbourhoods, the more likely it will be that shooting-incident ties will take shape across the neighbourhoods. This finding must be interpreted with caution, as there are several possible explanations for the phenomenon. For instance, commercial land use and other resources influence individuals' daily movements across an urban landscape. The lack of resources

in disadvantaged areas affects residents' interactions with one another and residents' exposure to other areas, thus entailing the spread of criminal behaviour to other neighbourhoods. Another possibility is that the positive association between movement flows and the co-movement of violent crime is a function of criminals' commuting between each other's residential neighbourhoods. People's tendency to practice homophily at the individual level increases the likelihood that criminals residing in spatially different—but demographically similar—neighbourhoods will establish various positive relationships with one another, thereby promoting criminal activity that a non-resident of a neighbourhood carries out in that neighbourhood. Considering the city as a network of neighbourhoods can improve how we understand the dynamics of violence and, in particular, how social issues (e.g., racial segregation, concentrated poverty) affect individuals' mobility and, in turn, may help to understand the co-movement of violence.

6.1 Thesis Summary and Key Findings

6.1.1 The Shifts and Broadens of the Network Concept Across Chapters

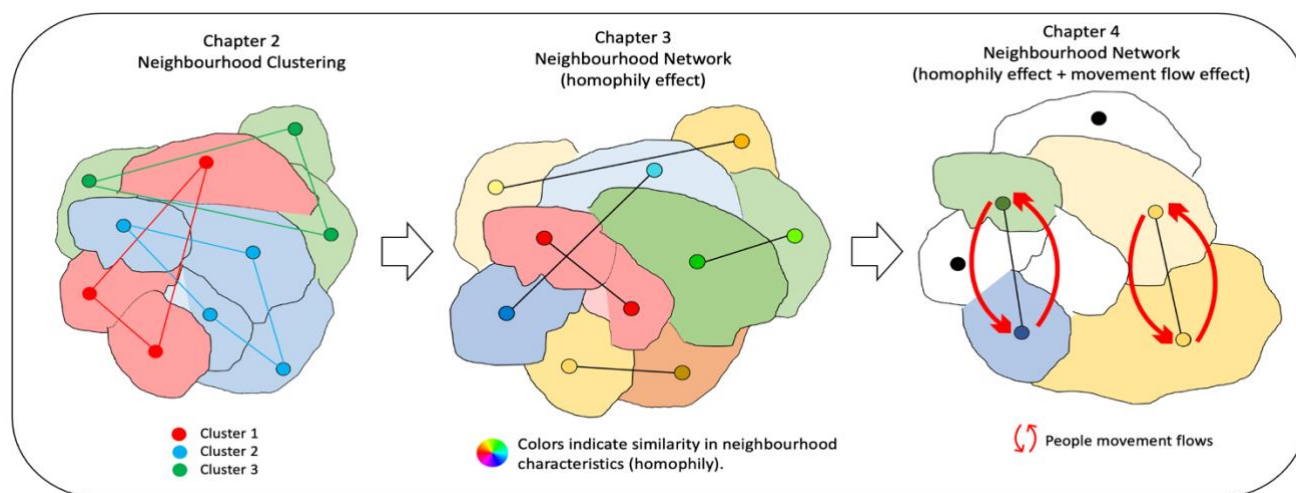


Figure 19 The thesis's comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in crime.

In chapter 2, as shown in Figure 19, using clustering analysis, I started the exploration of the interdependencies of crime dynamics between neighbourhoods and how these have implications for how we understand crime. For example, there appeared to be structural differences in the neighbourhood clusters membership and the determinants of crime between neighbourhoods with different crime trajectories. Whilst clustering neighbourhoods on the basis of similarity of crime trajectories, these clusters remain a ‘black box’ in the sense that the much of the underlying structures of interdependence remain hidden because we cannot observe the pairwise connections between neighbourhoods or analyse the factors that drive them – we can only observe and explain group-level connections between clusters of neighbourhoods.

Thus, in chapter 3, I continued the investigation of neighbourhood interdependencies by exploring the structure of inter-neighbourhood linkages. I conceptualized the neighbourhood interdependencies in crime dynamics as a network, where each neighbourhood is a node and the links between them represent co-movement of crime rates. The focus of this chapter was on the structure and drivers of these interdependencies by examining the impact of (i) spatial proximity (ii) ‘social frontiers’ and (ii) homophily—also known as ‘assortative mixing’— on the co-movement of crime and whether neighbourhoods that are similar in terms of their characteristics such as the levels of poverty and ethnic mix are more likely to have closely entwined crime trajectories.

Common vulnerabilities and socio-economic features between any pair of neighbourhoods will co-movements in crime rates more likely, as will underlying social networks between these neighbourhoods. These social networks, I argue, will give rise to, and be reinforced by, strong population flows between them. In chapter 4, therefore, I built on the network structures approach by exploring the role of populations flows in determining interdependencies in neighbourhood

violence, focusing in particular on the co-movements of shooting incidents. When combined, these features provide a comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in crime.

6.1.2 Summaries of Thesis Chapters

Table 9 highlights the key concepts, questions and findings of the component parts of the thesis.

Table 9 Summary of Chapter 2, Chapter 3, and Chapter 4

	Chapter 2	Chapter 3	Chapter 4
Key concepts explored	Clusters of neighbourhoods' crime trajectories.	The impact of assortative mixing and spatial proximity on the co-movement of property crime.	The impact of assortative mixing, spatial proximity, and people movement flows on the co-movement of violence.
Research questions	<ol style="list-style-type: none"> 1. Do neighbourhoods, in a given city, experience disparate crime trajectories? 2. Are there systematic drivers of group membership? 3. Are there structural differences in the determinants of crime levels across the different neighbourhood groups? 	<ol style="list-style-type: none"> 1. To what extent does homophily and spatial proximity explain the co-movement of property crime across Cleveland's neighbourhoods? 2. To what extent does social frontier and the historical discrimination of redlining maps explain the co-movement of property crime across Cleveland's neighbourhoods? 	<ol style="list-style-type: none"> 1. What is the impact of people's movement flows on the co-movement of shooting incidents across Chicago's neighbourhoods? 2. To what extent does homophily and spatial proximity explain the co-movement of shooting incidents across Chicago's neighbourhoods?
Data	<ul style="list-style-type: none"> • Property crimes between 2010 and 2017 in Cleveland, OH, USA. • Neighbourhood characterises. 	<ul style="list-style-type: none"> • Property crimes between 2010 and 2017 in Cleveland, OH, USA • Neighbourhood characterises. 	<ul style="list-style-type: none"> • Shooting incidents between 2014 and 2020 in Chicago, IL, USA • Neighbourhood characterises.
Methods	<ul style="list-style-type: none"> • K-Means. • Multinomial Logistic Regression. • Multiple Regression. 	<ul style="list-style-type: none"> • Social Network Analysis. • ERGMs. 	<ul style="list-style-type: none"> • Social Network Analysis. • ERGMs.
Key findings	<ul style="list-style-type: none"> • Identified three groups of neighbourhoods with disparate crime trajectories: Group 1 (increase by 48%), Group 2 (decrease by 22%) and Group 3 Stable (no major change). • Clusters can significantly affect the coefficients of simple regression-based models of crime. 	<p>Four mechanisms driving neighbourhoods' co-movement of property crime:</p> <ul style="list-style-type: none"> • Spatial Proximity. • Homophily. • Social frontiers. • Historical discrimination (1930s redlining maps) 	<p>Three mechanisms driving neighbourhoods' co-movement of violence:</p> <ul style="list-style-type: none"> • Spatial proximity. • Homophily. • Direct interactions (through people movement flows).

Second Chapter Summary

As a way into exploring these issues, in Chapter 2, I applied clustering approach to neighbourhood crime trajectories and demonstrated how these clusters can significantly affect the coefficients of simple regression-based models of crime. I discussed how scholarship on crime trajectories typically overlooks the socioeconomic and demographic characteristics of neighbourhoods that link these urban communities together and that influence their crime trajectories. Later in Chapter 2, I explored the effects of neighbourhood characteristics on neighbourhoods' membership in crime-trajectory clusters, attempting to discern whether or not some of these characteristics are systemic drivers of group membership. In addition, I explored how these drivers of group membership might shape both current and future crime-modelling practices. To this end, I focused especially on how the impact of independent variables might vary according to the type of neighbourhood group they are present in.

The data for Chapter 2 came from the city of Cleveland, Ohio, and concerned property crimes that had occurred between 2010 and 2017. Using a three-step approach, I analysed the data and consequently identified three groups of neighbourhoods, with each one distinguishable by its crime trajectory over the study period. Group 1 consisted of neighbourhoods experiencing an increase in property-crime trajectories, with a relative mean increase of 48%. Group 2, its member neighbourhoods were experiencing a relative mean decrease of slightly more than 22% in property crime. As for Group 3's neighbourhoods were experiencing no major relative change in property crime. These findings provide insights into the nature of crime trajectories in macro places (specifically, neighbourhoods). Consistent with prior research on micro-place crime trajectories (e.g., Weisburd et al., 2004, Groff et al., 2010, Curman et al., 2015), the findings in Chapter 2

confirmed that, similar to micro places, a city's neighbourhoods can experience various crime trajectories.

The existing research on crime and place has focused predominantly on the trajectories of crime in micro places and has typically overlooked what makes neighbourhoods exhibit highly similar crime trajectories. Hence, my second aim in the first chapter was to investigate whether there are systematic drivers of group membership. I brought a broad range of variables together into a single model through which I was able to examine their influence on neighbourhoods' membership in one of the three aforementioned crime-trajectory groups. My analysis revealed notable differences among the analysed variables regarding their influence on group membership. For example, some variables were found to reduce the probability of a neighbourhood being in one group, but the likelihood of being in the other group reduced by different variables. Similarly, some variables were found to increase the likelihood of being in a one group, but do not have an impact on the other group membership. These findings show that the membership of different neighbourhood groups is influenced by different factors. These findings appear to be consistent with our theory that neighbourhoods are linked to one another insofar as they possess one or more closely matching in some characteristics. These characteristics could be part of a mechanism that causes neighbourhoods to respond similarly to external changes.

These findings raised the question of whether or not there are structural differences in the determinants of crime levels across the three neighbourhood groups. If indeed this causation is in play, it may affect the way crime modelling should be approached. Hence, my third aim in this research was to explore whether or not the determinants of crime rates differed across the three groups of neighbourhoods. This possibility is supported by the results of my multiple regression analysis and the interaction test, which revealed that some neighbourhood characteristics exhibited

different effects in different groups. As the results demonstrate, three of the neighbourhood characteristics (i.e., poverty, family disruption and business addresses) significantly and positively associated with crime rate. However, significant differences of their effect seen in the interaction model results. Thus, the interaction test results confirmed that same variable may operate differently in different groups. For example, a significant difference in all significant variables was found between group 2 and group 1. Also, a significant difference was found in the poverty rate between group 3 and group 1. In other words, the results show that poverty, family disruption and business addresses boot crime rate but they boot crime rate in group 1 by substantially more than boot crime rates in group 2. In summary, while some variables showed a significant impact on the crime level, their effect was significantly different across groups. The results presented herein should be interpreted with caution. First of all, the differences in factors' possible effects on neighbourhood-group crime levels might reflect differences in crime opportunities across neighbourhoods (Weisburd et al., 2012). Consistent with my initial theoretical hypotheses, the above-mentioned differences may reflect the existence of as-yet poorly understood underlying factors that drive crime trajectories in those residential areas.

Third Chapter Summary

The third chapter addressed the seldom studied topic of neighbourhoods' interdependencies beyond the role of geographical proximity. Prior research has linked three areas of interest—spatial clustering, the similarity of crime trajectories, and the stability of crime trajectories—over time in spatial units such as street segments and neighbourhoods. However, the mechanisms driving neighbourhoods' crime co-movement have not been explored with statistical methods that can account for dependency between observational units. Hence, in this chapter I continued the investigation of neighbourhood interdependencies by exploring the structure of these

inter-neighbourhood linkages. One method that *can* account for dependency is statistical network analysis, and it served as the foundation for the present study, which—as far as I know—is the first to explicitly investigate a broad range of factors that drive the co-movement of crime between neighbourhoods. Using property-crime data from the American city of Cleveland, Ohio, I examined the extent to which homophily explains the underlying connections between neighbourhoods and how homophily affects the co-movement of crime. The findings indicate that both spatial and social proximity play a dominant role in driving the underlying crime-related connections between neighbourhoods

A central aim of mine in the third chapter was to extend the neighbourhood-network literature by exploring networks of crime co-movement and, more importantly, by paying careful attention to the underlying mechanisms driving similar crime trajectories across neighbourhoods. The findings of this chapter indicate that two neighbourhoods are more likely to be linked if they are spatially close. However, spatial proximity is not the only factor strongly associated with the formation of crime-related ties between neighbourhoods. The findings further indicate that the more similar two neighbourhoods are in terms of socioeconomic and demographic characteristics, the more likely they are to be linked.

Interestingly, the analysis of the data shows that heterogeneity at the level of disadvantage was associated with an increase in the likelihood of crime co-movement ties between neighbourhoods. In contrast to co-offending network research (Schaefer, 2012, Papachristos and Bastomski, 2018b), the research presented in this chapter shows that similarity in the disadvantage level was associated with a decrease in the likelihood of tie formation between neighbourhoods. That is, ties were more likely to exist between neighbourhoods possessing dissimilar levels of disadvantage, indicating patterns of heterophily in tie formation. To further explore this

relationship, I defined an additional model, which enabled me to control for contiguity and to measure the possible effects of social frontiers. The heterophily significant effect remained stable even after contiguity was controlled for, indicating that the existence of these ties is more likely due to effect of social frontiers between adjacent neighbourhoods. This finding is consistent with those of previous studies indicating that disadvantage in geographically proximate neighbourhoods affects—or at least is very significantly associated with—crime rates and victimization in proximate neighbourhoods (Morenoff et al., 2001, Peterson and Krivo, 2009, Peterson et al., 2010, Crowder and South, 2011, Vogel and South, 2016). Finally, my finding that social frontier may promote crime co-movement tie formation is in line with previous research that observed significant associations between social frontiers and high crime rates in dissimilar neighbourhoods. For example, similar contiguous neighbourhoods have been found to experience lower crime rates than dissimilar contiguous neighbourhoods (Hirschfield et al., 2014, Dean et al., 2019).

Another important finding in my research for Chapter 3 was that crime co-movement ties were more likely to be between “redlined” neighbourhoods than between neighbourhoods that fell outside that classification. This finding broadly supports earlier work that found an association between redlined neighbourhoods and high crime rates in three different cities (Anders, 2019). These associations may be the result of several mechanisms. In the United States, the historical redlining of neighbourhoods was based on criteria such as location, disadvantage, and the proportion of residents belonging to a racial minority (Anders, 2019). The long-term effects of this stigma have contributed to racial segregation, lower income, and lower educational attainment, all of which are in turn associated with high crime rates (Billings et al., 2014, Anders, 2019). Another possible explanation for redlining-based homophily is the structural isolation of redlined neighbourhoods. In these areas, ex-offenders, stigmatized by their criminal record, struggle to find

jobs and housing options, and often resign themselves to staying in their previous neighbourhoods or to moving to similarly disadvantaged neighbourhoods (La Vigne, 2003, Kirk, 2009). The result of these systemic restrictions is that redlined neighbourhoods have relatively few ties to other communities.

Fourth Chapter Summary

The fourth chapter addresses the potential mechanisms responsible for the co-movement of shooting incidents beyond the role of geographical proximity. In recent decades, a great amount of criminology research has addressed both the concentration and the distribution of violence, especially in urban settings. In this regard, previous empirical studies that have emphasized spatial clustering of violent crime, the non-randomly distributed of violence across neighbourhoods, and the spills over of violent crime into nearby neighbourhoods. Previous empirical studies examined the neighbourhood characteristics that were thought to entail higher violence rates in multiple neighbourhoods in a given city. However, beyond the factor of geographical proximity, little has been revealed about the specific mechanisms responsible for these similarities.

In this chapter, I draw on previous research examining the relationship between neighbourhood networks and crime in order to answer two research questions: (1) What is the impact of people's movement flows on the co-movement of shooting incidents across Chicago's neighbourhoods? (2) To what extent does homophily and spatial proximity explain the co-movement of shooting incidents across Chicago's neighbourhoods? The main novel contribution of the present study lies in its examination of both people's movement flows across neighbourhoods and homophily—each of which is treated, herein, as a possible underlying mechanism shaping the co-movement of violence across neighbourhoods.

The study was approached by analysing the co-movement of shooting incidents over the six-year period between 2014 and 2020 in the major US city of Chicago. Using shooting-incident data, a mobile phone origin–destination (MPOD) dataset, and US census data, I estimated a set of exponential random graph models (ERGMs) to investigate the attributes of neighbourhoods that foster shooting co-movement.

The findings of this study show the homophily effect of socioeconomics between neighbourhoods in ways that increase the probability of shooting ties. In particular, similarity in poverty levels and in the black and youth segments of a population seem to significantly increase the likelihood that shooting-incident ties will form between neighbourhoods; and where such ties exist, the trajectories of shooting incidents are likely to be similar, as well. These findings are consistent with mechanisms that previous research discussed in relation to co-offending networks. For instance, similarity in socioeconomic characteristics was found to increase the likelihood of criminal connections between neighbourhoods (Schaefer, 2012, Papachristos and Bastomski, 2018a).

In this study, I have also uncovered evidence that people’s movement flows across neighbourhoods significantly influence the co-movement of shooting incidents. That is, the larger a movement flow is between neighbourhoods, the more likely it will be that shooting-incident ties will take shape across the neighbourhoods. This finding must be interpreted with caution, as there are several possible explanations for the phenomenon. For instance, commercial land use and other resources, the lack of resources in disadvantaged areas, and the high-risk places such as illegal-drug markets and liquor stores affect the individuals’ daily movements across urban landscape and residents’ interactions and exposure to other areas that may entailing the spread of criminal behaviour to other neighbourhoods.

Also, the findings suggest a role for spatial proximity in explaining why neighbourhoods shooting incidents move together. However, when remove ties to adjacent tracts removed; that shows that proximity still matters, but much less so - and flows of movement are still a core part of why proximity matters. Hence, neighbourhoods move together in part because they have similar composition, and in part because of the movement flows of people tie neighbourhoods together.

6.2 Contributions and Implications

My ‘three-paper’ thesis makes several original contributions to the existing crime-and-place literature. First, to my knowledge, no previous research has used social network analysis to investigate why some neighbourhood crime rates move in tandem. This omission in the literature is important not only for methodological reasons but also because network analysis offers a powerful conceptual framework for thinking about the co-movement of crime. Second, conceptualizing the co-movement of crime as a type of network strengthens the possibility that we can create reasonably comprehensive portraits of neighbourhood crime co-movement, and provides insights into the attributes and possible causal factors linking similar neighbourhoods to one another. Third, in this thesis, I examined the added value that arises when one considers mobility flows, homophily, social frontiers, and the historical discrimination of redlining maps. In these regards, my overall research findings constitute evidence that the aforementioned factors may serve as underlying mechanisms that drive the co-movement of crime across neighbourhoods.

A number of implications have emerged from this research for policy, theory, and methodology. At the policy level, my findings concerning crime trajectory clustering should reinforce the view that, to be efficient and successful, policing and crime prevention strategies should consider the crime trajectories that characterize clusters of neighbourhoods. If law enforcement becomes better at recognizing similarities among neighbourhoods, it can more

efficiently strategize solutions to persistent, seemingly intractable crime problems (Wheeler et al., 2016).

A second policy implication stems from my thesis finding that the social proximity of neighbourhoods may affect the crime dynamics, regardless of the spatial distance between them. Therefore, policies and interventions should avoid targeting one neighbourhood in isolation from other neighbourhoods. A corollary of this principle can be stated as follows: crime prevention policy that pays attention to highly connected disadvantaged neighbourhoods may help to reduce crime rates in fairly large urban areas (Graif et al., 2021). That is, in order to combat crime, it may be necessary to apply crime prevention strategies in all neighbourhoods that have crime co-movement ties and criminogenic traits, not just those with high crime rates or in close proximity.

At the theoretical level, the findings of my thesis advance the crime and space theories by showing that a neighbourhood's characteristics are not only associated with local crime rates, but also affect the network structure of neighbourhood interdependence and their co-movement of crime. Furthermore, this research shows for the first time how social frontiers may drive crime co-movement across neighbourhoods, lending support to the assertion that social frontiers affect crime rates (Dean et al., 2019).

At the methodological level, my thesis has implications for two areas. First, my finding that the effects of neighbourhood characteristics vary across the three neighbourhood groups should have significant implications for researchers' methodological understanding of how they model crime data. My findings suggest that much of the crime research conducted today cannot rigorously rely on a single model, which by definition suggests that crime rates have universal causes; the research community needs more models possessing more complexity. Hence, researchers' knowledge of crime trajectories and of the possible systemic drivers of group

membership may significantly influence the modelling of crime data, leading in turn to improved crime prediction.

The second implication that my thesis has at the methodological level is the novelty of this three-fold research's approach to studying the co-movement of crime across neighbourhoods. Social-network analysis not only helped uncover what conventional methods would have overlooked (the crime co-movement network structure), but also identified potential underlying mechanisms driving the dynamics of crime across neighbourhoods. These mechanisms may very well cause neighbourhoods to experience similar trajectories of crime. Researchers developing future novel methods for conducting studies in this field would do well to consider the factors of homophily, spatial proximity, social frontiers, and movement flows—all four of which received careful attention in this three-fold study.

Moreover, this work provides a foundation for developing models that help us understand how crime cascades across neighbourhoods. That is, building the crime co-movement network and uncovering the possible mechanisms driving crime co-movement ties between neighbourhoods was the first step to developing crime cascades models, and the next step is building directed networks to understand the flows and the sequence of cascades across geographic areas. Directed links between neighbourhoods or another geographic area can show that changes in crime in one area affect changes in crime in another area. For example, if changes in crime in neighbourhood A precede changes in crime in neighbourhood B, which in turn precedes changes in crime in neighbourhood C. In this sense, we can think of crime changes in neighbourhood A cascading down to neighbourhood B and then to neighbourhood C. Developing such models allows police departments and professionals to predict and anticipate where the next crime is likely to increase. When police departments become able to predict where crime starts (crime initiator) and ends

(crime receiver or repeater), this will more likely increase the efficiency of police intervention and the allocation of crime prevention resources.

In conclusion, prior research in quantitative criminology research to date has tended to study the problem from two perspectives: an individual perspective and a context perspective. The individual perspective research commonly explores why some individuals, and not others, get involved in criminal activity. While the first perspective emphasizes people, the perspective of context considers the important role played by the characteristics and social processes in levels of crime within a geographic area. Hence, owing to the limitations identified in individual-centered criminology, the criminology of place has emerged as a perspective of considerable interest among criminologists. Prior research in place-centred criminology tended to focus on three research areas. First, cross sectional studies that explore the reasons for rates of crime being higher in some neighbourhoods than others. Second, longitudinal studies that study crime trajectories at different geographic scales. Third, studies that moved beyond a focus on the intra-neighbourhood setting to recognize the importance of connections between neighbourhoods in terms of crime dynamics. However, previous empirical research in the field of place-centred criminology has suffered from a number of limitations that are explained in chapter 1. This thesis contributes to the literature by (i) addressing the limitations of cross-sectional studies by studying the long-term patterns of crime within a geographic unit, which enhances the understanding of the development of crime over time. (ii) addressing the limitations of prior crime trajectory research by studying both the crime trajectories and the potential mechanisms that drive similarities between neighbourhoods' crime trajectories using social network analysis. The concept of conceptualizing the co-movement of crime as a type of network provides a more appropriate empirical framework for analysis and understanding of the crime dynamics across neighbourhoods. Although the individual perspective

is beyond the scope of this research, I believe that combining both the context and the individual perspectives will provide a more coherent and comprehensive conceptual framework for understanding the nature of inter-neighbourhood dependencies in crime.

6.3 Thesis Limitations and Challenges

Working on crime research requires that the researchers have access to crime data at a specific location over a sufficient period of time. Researchers can access such data from two main sources: police departments and open-data portals. Being an international student, I found it extremely difficult to gain access to data from police departments, as these institutions can be more closed than open and often hold sensitive data. Fortunately, police departments and other law-enforcement and justice institutions offer the public a variety of open-data resources. The ease of access characterizing these portals led me to rely heavily on open data for this thesis. Despite the clear benefits of open crime-related data, which are available from many cities around the world, this form of information is subject to several limitations including short time periods covered by the data—an obstacle that is particularly pronounced for specific types of crimes.

Hence, while this thesis provides a number of insights for practitioners and researchers alike, it is subject to a number of limitations. First, in conducting the research for this thesis, I encountered formidable difficulties collecting data related to crime and to neighbourhood characteristics. The extensive length of the periods I was researching only compounded these difficulties.

Second, the findings herein provide evidence that homophily is associated with the formation of crime co-movement ties. However, it is difficult to fully explain these associations owing to both the previously cited limitations of the data and the approach used in this study. In other words, it is difficult to fully explain the meaning of those connections or explaining why

such homophily and some characteristics foster the formation of ties between neighborhoods. Simply put, this line of research requires other approaches such as qualitative, ethnographic, or even cleverly developed mixed-methods approaches.

A third limitation is that the analysis was restricted by the availability and limitations of the open data, thus, only selected neighborhoods' characteristics were included in this study. Other characteristics that have been shown to foster connections between neighborhoods (e.g., relationships among street gangs, familial ties, or the distribution of governmental resources) were not included in the models due to these limitations.

A fourth limitation arises because of the unavoidable constraints on my time as a researcher, I focused on only two specific types of crime: property crimes and shooting incidents. For obvious reasons, the findings and observed patterns should not be generalized to other types of crime without concrete evidence that the generalization is compelling. Hence, these limitations highlight that further research should examine the extent to which such patterns hold under different types of crime, historical and geographic considerations.

Fifth, to assess the dynamics of violent crime in the fourth chapter, I relied exclusively on shooting incidents, which are quite distinct from other types of violent crime type. Thus, once again, this study's narrow scope hampers the generalizability of the study's findings: no single type of violent crime may represent the full picture of violence dynamics.

Lastly, I did not have an access to the individuals' mobility data for the study period, and my measures of movement flows were based on a single year (i.e., 2019). Hence, expanding the mobility data by even a few years might strengthen not only the generalizability of findings, but also the number and the depth of these findings, yielding potentially critical knowledge about the

patterns of people's movement flows over time and how changes in such patterns could influence the dynamics of crime.

6.4 Future Research

The aforementioned limitations have the following implications for future research. First, to improve the generalizability of findings, future research should evaluate and confirm the adopted research methods by applying them to data from various cities and by covering various types of crime. Second, future research should examine how well, if at all, the crime dynamic drivers hold in a range of historical and geographic contexts. Third, future research can improve on the current study by addressing multiple types of ties (e.g., co-offending and work commuting). The more comprehensive the crime co-movement factors are, the more comprehensive our understanding of crime co-movement will be. Fourth, no two cities are alike and many are quite dissimilar, especially in the United States. Thus, future research analysing the co-movement of crime across neighbourhoods would do well to move beyond the "one city per study" approach that I adopted in the current study (Cleveland for chapters 2 and 3; Chicago for chapter 4) and assess how drivers of crime dynamics vary across cities. This widening vista of cities can benefit future research in another way: the integration of far-flung cities into research on the co-movement of crime can clarify whether this co-movement is a function of similar circumstances in the disparate cities or a function of networks that extend across cities, much like the networks that extend across neighbourhoods.

Lastly, future research can extend the present research by developing a directed network which can point to promising directions in which law enforcement predicts where crimes are initiated in a given city and how they cascade across the city. Network analysis offers the potential to understand the nature of these crime cascades (Dean and Pryce slides 2018) and which attributes

of a neighbourhood make it more likely to be an initiator of crime trends. Note, however, there are other properties of network structures beyond neighbourhood characteristics and spatial proximity. Fox et al. (2021), for example, using data on person-level crime networks, finds that, “network individuals who are in a position to manage the flow of information in the network (betweenness centrality), regardless of their number of connections (degree centrality), are significantly more likely to be homicide and aggravated assault victims.” Similarly, the position of a node in a neighbourhood-level network in terms of how many connections a particular neighbourhood has (degree centrality) and the importance of that node in linking other parts of the network (betweenness centrality) may also be important in determining the likelihood of a neighbourhood being a catalyst node and the extent of the network-wide impact of any crime trends that originate there.

Reference

- AKERS, R. L. 1973. Deviant behavior: A social learning approach.
- ALBRECHT, H.-J. & MOITRA, S. 1988. Escalation and specialization. A comparative analysis of patterns in criminal careers. *Crime and criminal justice: criminological research in the 2nd decade at the Max Planck Institute in Freiburg*. Max-Planck-Inst. für Ausländisches und Internationales Strafrecht.
- ANDERS, J. P. 2019. The Long Run Effects of Transformational Federal Policies: Redlining, the Affordable Care Act and Head Start.
- ANSELIN, L. 2002. Mapping and analysis for spatial social science. *Center for Spatially Integrated Social Science, University of California, Santa Barbara, CA*.
- ANSELIN, L., COHEN, J., COOK, D., GORR, W. & TITA, G. 2000. Spatial analyses of crime. *Criminal justice*, 4, 213-262.
- AUERHAHN, K. 1999. Selective incapacitation and the problem of prediction. *Criminology*, 37, 703-734.
- BALLER, R. D., ANSELIN, L., MESSNER, S. F., DEANE, G. & HAWKINS, D. F. 2001. Structural covariates of US county homicide rates: Incorporating spatial effects. *Criminology*, 39, 561-588.
- BANNISTER, J., BATES, E. & KEARNS, A. 2018. Local variance in the crime drop: a longitudinal study of neighbourhoods in greater Glasgow, Scotland. *The British Journal of Criminology*, 58, 177-199.
- BARNETT, A. & LOFASO, A. J. 1985. Selective incapacitation and the Philadelphia cohort data. *Journal of Quantitative Criminology*, 1, 3-36.

- BAUMER, E., LAURITSEN, J. L., ROSENFELD, R. & WRIGHT, R. 1998. The influence of crack cocaine on robbery, burglary, and homicide rates: A cross-city, longitudinal analysis. *Journal of research in crime and delinquency*, 35, 316-340.
- BELLAIR, P. E. & BROWNING, C. R. 2010. Contemporary disorganization research: An assessment and further test of the systemic model of neighborhood crime. *Journal of research in crime and delinquency*, 47, 496-521.
- BERSANI, B. E., NIEUWBEERTA, P. & LAUB, J. H. 2009. Predicting trajectories of offending over the life course: Findings from a Dutch conviction cohort. *Journal of Research in Crime and Delinquency*, 46, 468-494.
- BILLINGS, S. B., DEMING, D. J. & ROCKOFF, J. 2014. School segregation, educational attainment, and crime: Evidence from the end of busing in Charlotte-Mecklenburg. *The Quarterly Journal of Economics*, 129, 435-476.
- BLUMSTEIN, A. 1995. Youth violence, guns, and the illicit-drug industry. *J. Crim. L. & Criminology*, 86, 10.
- BLUMSTEIN, A. & ROSENFELD, R. 1998. Explaining recent trends in US homicide rates. *The Journal of Criminal Law and Criminology (1973-)*, 88, 1175-1216.
- BRAGA, A. A. 2001. The effects of hot spots policing on crime. *The ANNALS of the American Academy of Political and Social Science*, 578, 104-125.
- BRAGA, A. A., PAPACHRISTOS, A. V. & HUREAU, D. M. 2010a. The concentration and stability of gun violence at micro places in Boston, 1980–2008. *Journal of Quantitative Criminology*, 26, 33-53.
- BRAGA, A. A., PAPACHRISTOS, V. A. & HUREAU, D. M. 2010b. The concentration and stability of gun violence at micro places in Boston, 1980–2008. *Journal of Quantitative Criminology*, 26, 33-53.
- BRANTINGHAM, P. J. & BRANTINGHAM, P. L. 1984. *Patterns in crime*, Macmillan New York.
- BRANTINGHAM, P. L. & BRANTINGHAM, P. J. 1990. Situational crime prevention in practice. *Canadian journal of criminology*, 32, 17-40.
- BRANTINGHAM, P. L. & BRANTINGHAM, P. J. 1999. A theoretical model of crime hot spot generation. *Studies on Crime & Crime Prevention*.
- BYRNE, J. M. & SAMPSON, R. J. 1986. Key issues in the social ecology of crime. *The social ecology of crime*.
- CLARKE, R. V. & CORNISH, D. B. 1985. Modeling offenders' decisions: A framework for research and policy. *Crime and justice*, 6, 147-185.
- COHEN, J. & TITA, G. 1999. Diffusion in homicide: Exploring a general method for detecting spatial diffusion processes. *Journal of Quantitative Criminology*, 15, 451-493.
- COHEN, L. E. & FELSON, M. 1979. Social change and crime rate trends: A routine activity approach. *American sociological review*, 588-608.
- COOK, P. J. & LAUB, J. H. 1998. The unprecedented epidemic in youth violence. *Crime and justice*, 24, 27-64.
- CORK, D. 1999. Examining space–time interaction in city-level homicide data: crack markets and the diffusion of guns among youth. *Journal of Quantitative Criminology*, 15, 379-406.
- CROWDER, K. & SOUTH, S. J. 2011. Spatial and temporal dimensions of neighborhood effects on high school graduation. *Social science research*, 40, 87-106.
- CURMAN, A. S., ANDRESEN, M. A. & BRANTINGHAM, P. J. 2015. Crime and place: A longitudinal examination of street segment patterns in Vancouver, BC. *Journal of Quantitative Criminology*, 31, 127-147.
- DEAN, N., DONG, G., PIEKUT, A. & PRYCE, G. 2019. Frontiers in residential segregation: Understanding neighbourhood boundaries and their impacts. *Tijdschrift voor economische en sociale geografie*, 110, 271-288.
- DEAN, N. & PRYCE, G. 2017. Is the housing market blind to religion? A perceived substitutability approach to homophily and social integration. *Urban Studies*, 54, 3058-3070.
- DIETZ, R. D. & HAURIN, D. R. 2003. The social and private micro-level consequences of homeownership. *Journal of Urban Economics*, 54, 401-450.
- ECK, J. E. & ECK, E. B. 2012. Crime place and pollution: Expanding crime reduction options through a regulatory approach. *Criminology & Public Policy*, 11, 281-316.
- FELSON, M. & BOBA, R. L. 2010. *Crime and everyday life*, Sage.
- FLANNERY, D. J., VAZSONYI, A. T. & WALDMAN, I. D. 2007. *The Cambridge handbook of violent behavior and aggression*, Cambridge University Press.
- GOTTFREDSON, M. R. & HIRSCHI, T. 1990. *A general theory of crime*, Stanford University Press.

- GRAIF, C., FREELIN, B. N., KUO, Y.-H., WANG, H., LI, Z. & KIFER, D. 2021. Network spillovers and neighborhood crime: A computational statistics analysis of employment-based networks of neighborhoods. *Justice Quarterly*, 38, 344-374.
- GRAIF, C., GLADFELTER, A. S. & MATTHEWS, S. A. 2014. Urban poverty and neighborhood effects on crime: Incorporating spatial and network perspectives. *Sociology compass*, 8, 1140-1155.
- GRAIF, C., LUNGEANU, A. & YETTER, A. M. 2017. Neighborhood isolation in Chicago: Violent crime effects on structural isolation and homophily in inter-neighborhood commuting networks. *Social networks*, 51, 40-59.
- GRAIF, C. & MATTHEWS, S. A. 2017. The long arm of poverty: extended and relational geographies of child victimization and neighborhood violence exposures. *Justice quarterly*, 34, 1096-1125.
- GREEN, B., HOREL, T. & PAPACHRISTOS, A. V. 2017. Modeling contagion through social networks to explain and predict gunshot violence in Chicago, 2006 to 2014. *JAMA internal medicine*, 177, 326-333.
- GROFF, E. R. & LA VIGNE, N. G. 2001. Mapping an opportunity surface of residential burglary. *Journal of Research in Crime and Delinquency*, 38, 257-278.
- GROFF, E. R. & LOCKWOOD, B. 2014. Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *Journal of Research in Crime and Delinquency*, 51, 277-314.
- GROFF, E. R., WEISBURD, D. & YANG, S.-M. 2010. Is it important to examine crime trends at a local "micro" level?: A longitudinal analysis of street to street variability in crime trajectories. *Journal of Quantitative Criminology*, 26, 7-32.
- HANDCOCK, M. S., HUNTER, D. R., BUTTS, C. T., GOODREAU, S. M. & MORRIS, M. 2008. statnet: Software tools for the representation, visualization, analysis and simulation of network data. *Journal of statistical software*, 24, 1548.
- HARCOURT, B. E. & LUDWIG, J. 2006. Broken windows: New evidence from New York City and a five-city social experiment. *U. Chi. L. Rev.*, 73, 271.
- HARDING, D. J. 2010. *Living the drama: Community, conflict, and culture among inner-city boys*, University of Chicago Press.
- HEITGERD, J. L. & BURSİK JR, R. J. 1987. Extracommunity dynamics and the ecology of delinquency. *American Journal of Sociology*, 92, 775-787.
- HIPP, J. R. 2007. Income inequality, race, and place: Does the distribution of race and class within neighborhoods affect crime rates? *Criminology*, 45, 665-697.
- HIRSCHFIELD, A., BIRKIN, M., BRUNSDON, C., MALLESON, N. & NEWTON, A. 2014. How Places Influence Crime: The Impact of Surrounding Areas on Neighbourhood Burglary Rates in a British City. *Urban Studies*, 51, 1057-1072.
- HUQ, A. Z. & RAPPAPORT, J. 2022. Symposium Introduction: This Violent City? Urban Violence in Chicago and Beyond. *The University of Chicago Law Review*, 89, 303-321.
- Kramer, R.C., 1984. Critical Criminology, Traditional Crime, and Public Policy. *J. Soc. & Soc. Welfare*, 11, p.252.
- KIRK, D. S. 2009. A natural experiment on residential change and recidivism: Lessons from Hurricane Katrina. *American Sociological Review*, 74, 484-505.
- KONDO, M. C., ANDREYEVA, E., SOUTH, E. C., MACDONALD, J. M. & BRANAS, C. C. 2018. Neighborhood interventions to reduce violence. *Annual review of public health*, 39, 253-271.
- KRIVO, L. J. & PETERSON, R. D. 1996. Extremely disadvantaged neighborhoods and urban crime. *Social forces*, 75, 619-648.
- LA VIGNE, N. G. 2003. A portrait of prisoner reentry in Illinois.
- LARSEN, D. A., LANE, S., JENNINGS-BEY, T., HAYGOOD-EL, A., BRUNDAGE, K. & RUBINSTEIN, R. A. 2017. Spatio-temporal patterns of gun violence in Syracuse, New York 2009-2015. *PLoS One*, 12, e0173001.
- Leenders, R.T.A., 2002. Modeling social influence through network autocorrelation: constructing the weight matrix. *Social networks*, 24(1), pp.21-47.
- LOEFFLER, C. & FLAXMAN, S. 2018. Is gun violence contagious? A spatiotemporal test. *Journal of quantitative criminology*, 34, 999-1017.
- LOFTIN, C. & HILL, R. H. 1974. Regional subculture and homicide: An examination of the Gastil-Hackney thesis. *American Sociological Review*, 714-724.
- MARSDEN, P. V. & HURLBERT, J. S. 1988. Social resources and mobility outcomes: A replication and extension. *Social forces*, 66, 1038-1059.

- MCPHERSON, M., SMITH-LOVIN, L. & COOK, J. M. 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology*, 27, 415-444.
- MEARS, D. P. & BHATI, A. S. 2006. No community is an island: The effects of resource deprivation on urban violence in spatially and socially proximate communities. *Criminology*, 44, 509-548.
- MESSNER, S. F., ANSELIN, L., BALLER, R. D., HAWKINS, D. F., DEANE, G. & TOLNAY, S. E. 1999. The spatial patterning of county homicide rates: An application of exploratory spatial data analysis. *Journal of Quantitative criminology*, 15, 423-450.
- MIETHE, T. D. & MEIER, R. F. 1994. *Crime and its social context: Toward an integrated theory of offenders, victims, and situations*, Suny Press.
- MORENOFF, J. D. & SAMPSON, R. J. 1997. Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970–1990. *Social forces*, 76, 31-64.
- MORENOFF, J. D., SAMPSON, R. J. & RAUDENBUSH, S. W. 2001. Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, 39, 517-558.
- MUELLER, B. & BAKER, A. 2017. Drop in gang violence drove New York City shootings below 1,000 in 2016. *New York Times*. *New York City*, 3.
- MURPHY, A. K. & WALLACE, D. 2010. Opportunities for making ends meet and upward mobility: Differences in organizational deprivation across urban and suburban poor neighborhoods. *Social Science Quarterly*, 91, 1164-1186.
- PAPACHRISTOS, A. V. 2009. Murder by structure: Dominance relations and the social structure of gang homicide. *American journal of sociology*, 115, 74-128.
- PAPACHRISTOS, A. V. & BASTOMSKI, S. 2018a. Connected in crime: The enduring effect of neighborhood networks on the spatial patterning of violence. *American Journal of Sociology*, 124, 517-568.
- PAPACHRISTOS, A. V., BRAGA, A. A., PIZA, E. & GROSSMAN, L. S. 2015. The company you keep? The spillover effects of gang membership on individual gunshot victimization in a co-offending network. *Criminology*, 53, 624-649.
- PAPACHRISTOS, A. V., HUREAU, D. M. & BRAGA, A. A. 2013. The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence. *American Sociological Review*, 78, 417-447.
- PAPACHRISTOS, V. A. & BASTOMSKI, S. 2018b. Connected in crime: The enduring effect of neighborhood networks on the spatial patterning of violence. *American Journal of Sociology*, 124, 517-568.
- PARK, R. E. & BURGESS, E. W. 1925. *The City: Suggestions for Investigation of Human Behavior in the Urban Environmen.*, University of Chicago Press.
- PETERSON, R. D. & KRIVO, L. J. 1993. Racial segregation and black urban homicide. *Social Forces*, 71, 1001-1026.
- PETERSON, R. D. & KRIVO, L. J. 2009. Segregated spatial locations, race-ethnic composition, and neighborhood violent crime. *The Annals of the American Academy of Political and Social Science*, 623, 93-107.
- PETERSON, R. D. & KRIVO, L. J. 2010. *Divergent social worlds: Neighborhood crime and the racial-spatial divide*, Russell Sage Foundation.
- PETERSON, R. D., KRIVO, L. J. & HAGAN, J. 2010. *Divergent social worlds: Neighborhood crime and the racial-spatial divide*, Criminal Justice Research Center, Ohio State University, United States.
- PETERSON, R. D., KRIVO, L. J. & HARRIS, M. A. 2000. Disadvantage and neighborhood violent crime: Do local institutions matter? *Journal of research in crime and delinquency*, 37, 31-63.
- Radil, S.M., Flint, C. and Tita, G.E., 2010. Spatializing social networks: Using social network analysis to investigate geographies of gang rivalry, territoriality, and violence in Los Angeles. *Annals of the Association of American Geographers*, 100(2), pp.307-326.
- RAINE, A. 1993. Features of borderline personality and violence. *Journal of Clinical Psychology*, 49, 277-281.
- RALEIGH, E. & GALSTER, G. 2015. Neighborhood disinvestment, abandonment, and crime dynamics. *Journal of Urban Affairs*, 37, 367-396.
- RATCLIFFE, J. H. & RENGERT, G. F. 2008. Near-repeat patterns in Philadelphia shootings. *Security Journal*, 21, 58-76.
- SAMPSON, R. J. 2004. Networks and neighbourhoods. *Demos Collection*, 155-166.
- SAMPSON, R. J. 2012. *Great American city: Chicago and the enduring neighborhood effect*.
- SAMPSON, R. J. & GROVES, W. B. 1989. Community structure and crime: Testing social-disorganization theory. *American journal of sociology*, 94, 774-802.
- SAMPSON, R. J. & LAUB, J. H. 2003. Life-course desisters? Trajectories of crime among delinquent boys followed to age 70. *Criminology*, 41, 555-592.

- SAMPSON, R. J. & LEVY, B. L. 2020. Beyond residential segregation: mobility-based connectedness and rates of violence in large cities. *Race and social problems*, 12, 77-86.
- SAMPSON, R. J., MORENOFF, J. D. & GANNON-ROWLEY, T. 2002. Assessing “neighborhood effects”: Social processes and new directions in research. *Annual review of sociology*, 28, 443-478.
- SAMPSON, R. J., RAUDENBUSH, S. W. & EARLS, F. 1997. Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, 277, 918-924.
- SAMPSON, R. J. & SHARKEY, P. 2008. Neighborhood selection and the social reproduction of concentrated racial inequality. *Demography*, 45, 1-29.
- SCHAEFER, D. R. 2012. Youth co-offending networks: An investigation of social and spatial effects. *Social Networks*, 34, 141-149.
- SCHUERMAN, L. & KOBRIN, S. 1986. Community careers in crime. *Crime and justice*, 8, 67-100.
- SHARKEY, P. 2014. Spatial segmentation and the black middle class. *American Journal of Sociology*, 119, 903-954.
- SHARKEY, P. & MARSTELLER, A. 2022. Neighborhood Inequality and Violence in Chicago, 1965–2020. *U. CHI. L. REV.*, 89, 349, 351.
- SHAW, C. R. & MCKAY, H. D. 1942. Juvenile delinquency and urban areas.
- SHERMAN, L. W. 1995. Hot spots of crime and criminal careers of places. *Crime and place*, 4, 35-52.
- SHERMAN, L. W., GARTIN, P. R. & BUERGER, M. E. 1989. Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, 27, 27-56.
- SHORT, M. B., MOHLER, G. O., BRANTINGHAM, P. J. & TITA, G. E. 2014. Gang rivalry dynamics via coupled point process networks. *Discrete & Continuous Dynamical Systems-B*, 19, 1459.
- SMALL, M. L. & MCDERMOTT, M. 2006. The presence of organizational resources in poor urban neighborhoods: An analysis of average and contextual effects. *Social Forces*, 84, 1697-1724.
- Sutherland, E.H., Cressey, D.R. and Luckenbill, D.F., 1992. Principles of criminology. Altamira Press.
- SPELMAN, W. 1995. Criminal careers of public places. *Crime and place*, 4, 115-144.
- TAYLOR, R. 2018. *Breaking away from broken windows: Baltimore neighborhoods and the nationwide fight against crime, grime, fear, and decline*, Routledge.
- TITA, G.E. and RADIL, S.M., 2010. Making space for theory: the challenges of theorizing space and place for spatial analysis in criminology. *Journal of Quantitative Criminology*, 26(4), pp.467-479.
- TITA, G. & COHEN, J. 2004. Measuring spatial diffusion of shots fired activity across city neighborhoods. *Spatially integrated social science*, 171-204.
- TITA, G. & RIDGEWAY, G. 2007. The impact of gang formation on local patterns of crime. *Journal of Research in Crime and Delinquency*, 44, 208-237.
- TITA, G. E. & BOESSEN, A. 2011. Social networks and the ecology of crime: using social network data to understand the spatial distribution of crime. *The SAGE handbook of criminological research methods*, 128-142.
- TITA, G. E. & GREENBAUM, R. T. 2009. Crime, neighborhoods, and units of analysis: putting space in its place. *Putting crime in its place*.
- TOBLER, W.R., 1970. A computer movie simulating urban growth in the Detroit region. *Economic geography*, 46(sup1), pp.234-240.
- TRAN, V. C., GRAIF, C., JONES, A. D., SMALL, M. L. & WINSHIP, C. 2013. Participation in context: Neighborhood diversity and organizational involvement in Boston. *City & Community*, 12, 187-210.
- VOGEL, M. & SOUTH, S. J. 2016. Spatial dimensions of the effect of neighborhood disadvantage on delinquency. *Criminology*, 54, 434-458.
- WEISBURD, D., BUSHWAY, S., LUM, C. & YANG, S. M. 2004. Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology*, 42, 283-322.
- WEISBURD, D. & ECK, J. E. 2004. What can police do to reduce crime, disorder, and fear? *The annals of the American academy of political and social science*, 593, 42-65.
- WEISBURD, D., GROFF, E. R. & YANG, S.-M. 2012. *The criminology of place: Street segments and our understanding of the crime problem*.
- WEISBURD, D., MAHER, L., SHERMAN, L., BUERGER, M., COHN, E. & PETRISINO, A. 1992. Contrasting crime general and crime specific theory: The case of hot spots of crime. *Advances in criminological theory*, 4, 45-69.
- WEISBURD, D., MORRIS, N. A. & GROFF, E. R. 2009. Hot spots of juvenile crime: A longitudinal study of arrest incidents at street segments in Seattle, Washington. *Journal of quantitative criminology*, 25, 443-467.

- WELLMAN, B. 1999a. The network community: An introduction. *Networks in the global village: Life in contemporary communities*, 1-47.
- WELLMAN, B. 1999b. Networks in the Global Village Boulder. CO: Westview.
- WILSON, W. J. 1987. The Truly Disadvantaged: The Inner City. *The Underclass, and Public Policy*, 8.
- ZEOLI, A. M., PIZARRO, J. M., GRADY, S. C. & MELDE, C. 2014. Homicide as infectious disease: Using public health methods to investigate the diffusion of homicide. *Justice quarterly*, 31, 609-632.