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Micro-Place Homicide Patterns in Chicago

1965 – 2017

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Summary

This Springer brief examines 36,263 homicides in Chicago over a 53-year study period, 1965 through 2017, at micro-place grid cells of 150 m by 150 m. This study shows not only long-term historical patterns of homicides in Chicago, but also identifies the historical context of homicide in reference to the dramatic spikes in homicides in 2016–2017. We use several different inequality metrics as well as kernel density estimation maps to demonstrate that homicides were more clustered in the 1960s compared to later periods. We use zero inflated group-based trajectory models to demonstrate the long-term temporal stability of homicides at micro-places. Decreasing homicide trajectories show clear spatial clusters, one of which is heavily concentrated around places of former high-rise public housing.

Keywords Micro-places · Micro-level · Group-based trajectory models · Homicide · Hot spots · Gun violence · Chicago

Contents

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Chapter 1
Introduction

Abstract This brief chapter introduces the city of Chicago, including the crime of homicide over the past 53 years, and defines the framework for the remainder of the book. The authors outline the benefits and issues of longitudinal spatial analysis, including how this work contributes to the wealth of previous crime research that has been conducted in Chicago.

Keywords Chicago · Homicide · Crime clustering · Micro places · Spatiotemporal

Chicago is likely one of the most researched urban areas for its crime trends in space and time (Bernasco and Block 2010; Block 1977; Block 1979; 1987; Bursik and Webb 1982; Griffiths and Chavez 2004; Morenoff and Sampson 1997; Morenoff et al. 2001; Papachristos 2013; Papachristos et al. 2011; Sampson 2011; Sampson et al. 1997; Shaw and McKay 1969; Smith 2014; Stults 2010; Wilson 1990). This work expands on prior analysis of crime trends in Chicago at larger neighborhood levels by examining temporal homicide trends at micro places (Schnell et al. 2016).

Such analysis was in part spurned by the recent uptick of homicide in 2016. Were places that dramatically increased in homicide always historically high crime areas? Or did the homicide increase result in expanded areas of risk? To answer these questions, one needs to examine homicide from a historical lens and identify areas of historical high risk to identify changes from those typical patterns.

While crime and space has focused on neighborhood trends over much of the twentieth century, recent emphasis on crime at micro places has provided unique insight into what causes crime at particular places. Similar to the original work of Shaw and McKay (1969) on social disorganization, crime consistently concentrating at micro places over long periods of time signals that crime and place are tightly coupled (Weisburd et al. 2012). This can in turn promote new theories and explanations for spatial crime patterns that have not been examined by prior work.

Examining homicides at micro places over a very long period of time can additionally provide further evidence for the temporal stability of crime at micro places. The majority of prior studies replicating consistent patterns have focused on either all calls for service or all reported crimes (Curman et al. 2015; Weisburd et al. 2004; Wheeler et al. 2016). While some work has focused on crime-specific outcomes

A. P. Wheeler et al., *Micro-Place Homicide Patterns in Chicago*, SpringerBriefs in Criminology, https://doi.org/10.1007/978-3-030-61446-1_1

(Andresen et al. 2017; Braga et al. 2011; Braga et al. 2010), none of these studies have examined homicides. Given that hot spots of one type of crime do not imply a co-occurring hot spot of other crimes (Haberman 2017), it is important to examine whether such spatial and temporal trends hold for different types of crime over extended periods of time. While homicides represent the most serious of all crimes, they are difficult to conduct analysis on at micro places due to their sparsity. Analyzing over 35,000 homicides in a large city over such an extended period of time allows us to examine micro place patterns and clustering that is not viable for smaller samples.

Finally, examining homicides over such a long period of time, 53 years, provides a unique contribution to the crime and place literature. Most studies of temporal consistency of crime at micro places have been conducted during the period of the great crime decline (Blumstein and Wallman 2000). Examining homicides in Chicago over a longer time period allows us to better assess temporal stability in times of both rising and falling homicide trends. Additionally, given the recent large increase in homicides in Chicago, from 498 homicides in 2015 to 781 homicides in 2016. This begs the question of whether the recent homicide increase in 2016 was limited to a few spatial areas that historically had higher incidence of homicides, or did it spread to new locations that previously had lower levels of homicides.

Broadly, we focus our literature review on three different aspects relevant to the historical and contemporary analysis of homicide trends in Chicago. First, we detail the historical literature on crime in Chicago, which was the basis for the ecological study of crime and neighborhood levels. While much of the original Chicago school painted a picture of crime as spatially consistent, more contemporary analysis showed crime migrate away from the original zonal system outlined by Burgess (1925) to clusters of violence in different areas of the city (Bursik and Webb 1982).

Second, we focus on the more recent literature on micro places, in particular the temporal stability of micro place hot spots (Weisburd et al. 2004). While this work, rooted in crime pattern theory, suggests that places and micro crime generators creates long-term temporal consistency in crime at micro places, many of the samples were of much short time frames than we examine here and were mostly confined to time periods within the great crime decline. We provide a not only longer temporal sample here to examine but also a singular crime type, homicide, which has not been examined in such detail at such micro units before for such a long time period.

Third, we discuss recent advances in measuring crime clustering, which goes hand-in-hand with the measurement of long-term temporal stability. While prior work has examined such clustering at the neighborhood level in Chicago (Papachristos et al. 2018), we bring a renewed focus to this question both using longer more micro spatial measurements, but also pay close attention to the dramatic increase in homicide in Chicago in 2016 and 2017. Assessing clustering helps answer the question of whether recent homicide increases were concentrated in prior areas of high homicide risk or did they diffuse into a wider area. Such a question is surprisingly difficult to answer, due to the variety of ways in which one may estimate what it exactly means for crime to cluster.

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Chapter 2
Literature Review

Abstract This chapter reviews some of the history of Chicago homicide research, as well as the relevant criminological theories that are directly related to the evolution of our micro place homicide analysis. The history and issue of gang activity and public housing are introduced, including how both are related to Chicago homicides. This chapter explains why micro places and crime trajectory analysis was used to illustrate the long-term stability in Chicago's homicide patterns. The chapter concludes with a review of the historical research on crime clustering and how previous research guided the methods and analyses that were conducted in our 53-year study.

Keywords Chicago School · Informal social control · Social disorganization · Homicide patterns · Concentrated disadvantage · Public housing · Crime trajectories · Micro places · Crime clustering · Gang activity · Spatial resolution

Chicago School and Crime

While early examples of mapping crime in the 1800s can be traced back to France and England (Cook and Wainer 2012; Friendly 2007; Quetelet 1984), mapping various aspects of juvenile delinquency, crime, and other social ills in Chicago neighborhoods has greatly influenced criminology for the last 100 years (Block 2017). The most notable of these contributions is Shaw and McKay's (1969) social disorganization theory. Social disorganization theory was based on the observation that patterns of criminality in Chicago had shown spatial consistency in particular high crime neighborhoods, despite a complete change of different immigrant populations over the first 40 years of the twentieth century. This promoted a theory of succession and out-migration, with analogies to systems used to describe ecological habitats for wildlife. Shaw and McKay provided evidence that locations with higher levels of poverty, more frequent residential turnover, and more ethnic heterogeneity had relatively more crime in Chicago.

A. P. Wheeler et al., *Micro-Place Homicide Patterns in Chicago*, SpringerBriefs in Criminology, https://doi.org/10.1007/978-3-030-61446-1_2

An important innovation in this theory was the notion of informal social control – that individuals within communities were an integral component for controlling crime. This is opposed to formal control via the criminal justice system, such as via arrests or incarceration. Social disorganization presents a theory that individuals within neighborhoods, not the formal criminal justice system, are the main drivers of the extent and levels of crime (Sampson 2011). Individuals are more or less likely to intervene to prevent crime based on factors such as the extent to which they know and trust their neighbors. In areas in which high turnover occurs, it is difficult to develop formal ties necessary to intervene for the public good. This is also an explanation independent of individual characteristics of criminality. It described collective behavior of individuals, not people as individual and independent agents.

Additionally, Shaw and McKay illustrated the spatial distribution of crime tended to follow a particular concentric zonal pattern, with a lower incidence of crime in each subsequent ring. While the concentric zonal model was previously described by Ernest Burgess specifically for Chicago (Burgess 1925), with its inner most ring the Loop in Chicago, Shaw and McKay were the ones to show how crime followed such a pattern in Chicago and several other major cities in the United States (Shaw and McKay 1969). The theories emanating from the Chicago school were likely built both by the particular dynamics surrounding the scholars in Chicago in the early 1900s and by the careful accumulation and mapping of various data sources (Block 2017).

While later work would not invalidate social disorganization theory, the subsequent spatial stability of crime patterns in Chicago that was a central tenet of Shaw and McKay's work was later questioned. Bursik and Webb (1982), examining changes in delinquency rates and changes in residential population for 74 Chicago neighborhood areas from 1940 through 1970, show that areas with changing demographics post 1950 do show spatial changes in the distribution of delinquency. They hypothesize that such changes were the result of several factors relating to the African-American population. First, there was a dramatic increase in the African-American population in Chicago from 1940 (8%) to 1970 (33%). Second, African-Americans were relatively segregated in Chicago in an area known as the black belt, until 1950, when race-restrictive housing covenants were outlawed by the Supreme Court (Bursik and Webb 1982). After this, the African-American population spread out, and whites fled to the suburbs. Bursik and Webb (1982) believed such patterns of invasion and succession were much more accelerated than prevision transitions between other immigrant groups that Shaw and McKay studied. Additionally, Wilson (1990) believed the ability of African-Americans to choose where they lived more freely resulted in the black middle class fleeing from inner city Chicago during this same time period. This created extreme geographic concentration of disadvantage in particular African-American neighborhoods in Chicago.

Morenoff and Sampson (1997) examine later patterns of violent crime rates and population changes from 1970 through 1990 at the census tract level in Chicago. They find that areas with higher levels of homicide in the 1970s resulted in more population out-migration, in particular the white population out-migrated. With simultaneous slight gains in the African-American population during that same time period, this resulted in both a higher concentration of impoverished individuals and higher levels of racial segregation. They describe that while the Loop made sense for the inner ring of Burgess's concentric zonal model earlier in the century, a more appropriate center ring for this time period would be the black belt, which is south of the Loop. They also point out a similar cluster of homicides and concentration of poverty in the western part of the city (see also Block (1979) showing similar patterns).

Two additional long-term studies of homicide patterns at the neighborhood level in Chicago are Griffiths and Chavez (2004) and Stults (2010). Each uses the Chicago Homicide dataset and examines trajectories of homicide patterns at the census tract level. Using data from 1980 through 1995, Griffiths and Chavez identify unique trajectories for all homicides, as well as trajectories for homicide rates broken down by street gun homicides versus other weapon homicides. While the high crime trajectories for both types of homicide patterns show substantial spatial overlap, they each display unique temporal trajectories, with the rise in homicide mostly attributable to increases in gun homicide rates. Using homicide data from 1965 through 1995, Stults identified seven distinct trajectories, with several trajectories rising and falling over the time period.

These studies detailed here are of course not an exhaustive list of studies on homicides in Chicago neighborhoods over time. See Block (1977), Ye and Wu (2011), and Ferrandino (2017) for three additional examples.

More contemporary studies of crime and homicide patterns in Chicago have suggested additional processes which have implications for recent homicide trends. Morenoff et al. (2001) show that collective efficacy, the willingness of neighbors to intervene for the common good (Sampson et al. 1997), predicts homicide patterns for 1996 through 1998 in 343 neighborhood areas in Chicago, independent of prior homicide patterns and measures of concentrated disadvantage. Papachristos et al. (2011) examining homicides from 1991 through 2005 at the neighborhood cluster level suggest that gentrification, as measured via increasing numbers of coffee shops, predicted lower levels of homicides but resulted in more street robberies. Sampson (2011) mentions gentrification occurring in several neighborhoods as of 2010 as well, but also details the consistent levels of concentrated disadvantage in certain areas. He describes how these areas were more vulnerable to the great recession, resulting in higher levels of foreclosures, and subsequently contain many vacant lots.

Additionally, gang activity and high-rise public housing have been critical components to examining crime patterns in Chicago. Several of Chicago's high-rise public housing projects were notorious hot spots of crime, such as Cabrini-Green and the Robert Taylor Homes (Hunt 2009; Popkin et al. 2012; Smith 2014). For geographic reference, the Robert Taylor homes and Stateway Gardens were built within the area described as the black belt (Hunt 2009). Many of these projects were demolished after 2000 (although demolition of particular buildings in projects began earlier in the 1990s), and Popkin et al. (2012) attribute slight citywide declines in crime to such demolitions. However, Smith (2014), specifically examining gang-motivated homicides in Chicago from 1994 to 2005, suggests that public housing demolition increased the number of gang homicides. A possible reason, as detailed by Hagedorn and Rauch (2007), is that the demolition of large housing complexes and subsequent displacement of residents split up larger gangs into many smaller factions, resulting in higher levels of intra-gang violence (Papachristos 2013).

Micro Places and Crime Trajectories over Time

While much of the historical literature on space and crime was conducted at larger polities and neighborhoods (both specifically examining Chicago, as well as other criminological studies), more recent scholarship has focused on crime at micro places. There are three main empirical findings from this literature. One is that crime is concentrated among of small number of spatial units, such that 50% of the crime is concentrated at only 5% of the street segments in a variety of different samples (Weisburd 2015). This is described as Weisburd's Law of Crime Concentration. Identifying this clustering of crime at micro place hot spots has resulted in the success of hot spots policing (Braga et al. 2019).

The second empirical finding emanating from the focus on micro places is that such micro places tend to show long-term temporal stability in their crime patterns (Weisburd et al. 2004). So one can create hot spot maps that remain largely accurate over periods of decades. Similar to the Chicago school, this highlights potential spatial explanations for the reasons of these crime hot spots independent of individual person level characteristics.

The third empirical finding is that such hot spots tend to not be monolithic within high crime neighborhoods. Even places that at the neighborhood level appear to be high crime, there are micro places that experience relatively little crime. Simply traveling one block you can go from a high crime location to one that practically never experiences crime (Groff et al. 2010). This suggests that the neighborhood crime mechanisms specified in earlier research may be incorrect, as they would not provide reasonable explanation for such sharp crime contrasts over small micro areas.

The first research to examine crime at micro places over an extended time period was Weisburd et al. (2004) in Seattle. They initially examined crime incidents at the street segment level from 1989 through 2002. Crime incidents in Seattle displayed a similar level of spatial clustering over time, with 5% of the street segments consistently containing around 50% of the reported crime in every year. Additionally, they used group-based trajectory models to establish the long-term temporal stability of street segments over the time period. Many of the lower crime segments followed a flat temporal trajectory, and many of the high crime street segments mirrored the citywide crime decline over the period. Around 2% of the street segments increased over the time period though, bucking the overall crime decline experienced in Seattle. Using additional crime data in Seattle extending to 2004, Groff et al. (2010) examined the spatial distribution of the trajectories in reference to one another. They found that high crime trajectories were often right next to lower crime trajectories.

Similar results of temporal crime trends at micro places were replicated in several other studies. Examining calls-for-service in Vancouver, British Columbia, from 1991 to 2006 at the street segment level, Curman et al. (2015) found clusters of temporal trajectories that mimic the overall crime decline and also show similar reported trajectories whether one was using group-based trajectories models or k-means clustering for temporal data. In an additional study of the Vancouver data (although aggregated to both street segments and intersections), Andresen et al. (2016) show that crime trajectories for many different high-volume crimes cluster into similar trajectory solutions compared to all crimes in Vancouver, but each crime type tends to be in different spatial micro places. Wheeler et al. (2016) examining crime incidents in Albany, NY, from 2000 through 2013 at street units (a combination of street segments and intersections) similarly found that the micro place trajectories mirrored the citywide crime decline over the time period. For spatial analysis, Wheeler et al. (2016) showed that while high crime trajectory streets were often next to low crime ones, on average high crime groups tended to be nearer to other high crime groups, suggesting a potential spatial diffusion process. Using multilevel growth models in Boston to examine robberies (Braga et al. 2010a, b) and shootings (Braga et al. 2010a, b) from 1980 through 2008, Braga and colleagues show robberies tend to show long-term temporal stability at micro place street segments and intersections. But, they characterize the temporal patterns for shootings at micro places as either low crime or highly volatile.

Specific analyses of homicides over time at the micro place level are rarer. One exception is Periera et al. (2017), who examine homicides in Recife, Brazil, over the shorter time period of 2009 through 2013. They show that while crime is clustered at a minority of street segments, year to year correlations in total homicides are quite small, at around 0.05, and that certain areas contributed to the majority of the homicide decline.

Besides the Chicago homicide studies previously cited, there are three additional studies that analyze homicides over an extended period of time, but do so at larger aggregations that are more likely to be reflective of neighborhoods. But, these studies still have implications for examining micro place homicide patterns.

Zeoli et al. (2014) examined space-time clusters of homicides in Newark, New Jersey, from 1982 through 2008 at the census tract level and specifically separated out firearm and gang homicides from all homicides. They showed that each had particular temporal trends, with firearm clusters beginning earlier in the series, but gang homicides only clustering in the later 1990s. Robinson et al. (2009) examining homicides in Los Angeles at the zip code level from 1994 through 2002 attributes the majority of variance in homicides according to gang activity in each zip code. Valasik et al. (2017) also examine homicides in Los Angeles, focusing on one policing district, but distinguishing between gang and non-gang homicides. They find that gang homicides have more intense clustering in space and time relative to non-gang homicides.

Given Chicago's history of gang activity (Block 2000; Block and Block 1993; Papachristos et al. 2013; Smith 2014), it seems likely that the spatial distribution of gangs likely has implications for both temporal and geographic concentration of homicides over this long of a time period in Chicago. Prior work has found that violence tends to concentrate at the edges of gang territories (Brantingham et al. 2012; Papachristos et al. 2013) as well as the fact that one violent act can cause subsequent retaliation (Loftin 1986; Papachristos et al. 2013). This suggests that overlapping gang territories are likely to be micro places with higher levels of homicides and that the temporal trajectories may show episodic patterns of homicides over time.

While the prior review of the micro place literature was descriptive, it did not underline the potential theoretical mechanisms that result in such consistent crime patterns. The following section discusses the main theory with which criminologists explain those micro place hot spots – crime pattern theory and routine activities theory.

Crime Pattern Theory at Micro Places

While long-term analyses of homicides in Chicago are often more specifically focused on gang violence or neighborhood characteristics, explanations for long-term spatial clustering of general crime has often focused on the characteristics of particular places, as opposed to individuals. Such clustering of crime in space and time is often attributed to particular aspects of the built environment that influence where offenders and victims come into contact, thus generating spatial predictions based on routine activities theory (Cohen and Felson 1979; Eck and Weisburd 1995). Routine activities theory is that for a crime to occur, a potential offender and potential victim need to meet in space and time. In that case, and if there is additionally an absence of a guardian to prevent victimization, a criminal act is more likely to occur. Crime pattern theory is built off of routine activities theory, but actually describes spatial characteristics that are likely to promote more potential offenders and victims meeting within specific spatial areas.

Crime pattern theory (Brantingham and Brantingham 1995) predicts that there are two types of locations that tend to have a high prevalence of reported crime incidents. One is *crime generators*; these are locations that a large number of individuals attend to in their routine activities, such as a shopping mall, but the convergence of individuals has nothing directly to do with criminal activity. The other are *crime attractors*, these are locations that offenders specifically target due to the victims who lack guardianship, such as areas where drug dealing is common (Bernasco and Block 2010).

Such aspects of the built environment are generally fixed, and do not vary over short time periods. The reason for this is that land use zoning often restricts the locations where certain commercial establishments, like shopping malls, can locate (Fischel 2015). Such zoning rules were established in many American cities starting in the 1920s, with Chicago's originally established in 1923 (Twinam 2017). Thus, if crimes are greatly influenced by these crime generator and attractor locations, one would expect high crime micro places to be quite stable over long periods of time.

There are however exceptions to this, such as the opening and closing of train lines, or the building and demolition of public housing (Block and Davis 1996; Hunt 2009).

While crime pattern theory has a focus on places instead of people (who generate informal social control) in social disorganization theory, authors focusing on either theory often at least make passing note of concepts relevant to the other. In terms of social disorganization, Shaw and McKay (1969) mention that those who live in the interstitial zone are often competing with businesses and that those businesses bring about more physical and social disorder. Thus mixed zoning is likely to bring about higher level crimes according to both of these theories. Commercial establishments both draw in more individuals (so both potential offenders and potential victims), and given the lack of informal social control, both factors would be expected to increase crime (Smith et al. 2000). Given such equivocal predictions, it is often difficult (if not impossible) to distinguish whether a resulting spatial pattern is related specifically to either social disorganization or crime pattern theory. Spatial clustering would be expected to occur with either, and neither is specific enough to dictate precise levels of spatial clustering one would expect. It may also be the case that both theories could be acting concomitantly (Smith et al. 2000).

While crime pattern theory is also focused on micro places, whereas social disorganization is often focused on the meso neighborhood level, such spatial units of analysis may be a false dichotomy. One can have a neighborhood set of informal social control at a micro street unit level (Jacobs 1992; Taylor 1997). When individuals are asked what they consider their neighborhood territory, they often state nearby or the few streets nearby, as opposed to larger, labeled areas (Wheeler et al. 2019).

This additionally points to overlap between crime pattern and another popular theory of crime: broken windows theory (Wilson and Kelling 1982). Broken windows theory posits that physical and social disorder brings about fear of crime and that in turn degrades social disorganization over time. Physical and social disorder is often directly tied to commercial establishments (St Jean 2008; Taylor et al. 1995) or otherwise "busy places" in the Brantingham crime pattern framework.

While it isn't clear that all of these different factors either paint crime pattern theory as hopelessly confounded with other theories of crime or that they work in tandem to produce complicated crime patterns at the micro level (Smith et al. 2000), empirical evidence is strong that these factors are correlated with crime at micro places (Bernasco and Block 2010; Wheeler 2018a, b, 2019). They however are not entirely deterministic, as one can often find evidence of apartments or different commercial establishments that themselves have varying associations with crime (Eck et al. 2007).

Prior scholarship of crime patterns specifically in Chicago suggests several different potential micro place characteristics that may influence homicide patterns. For example, Papachristos et al. (2011) suggest that gentrification, as measured via increasing numbers of coffee shops, predicted lower levels of homicides but resulted in more street robberies. Block (1979) similarly found that homicide rates were negatively correlated with robberies in Chicago in the 1970s, but attributed the difference to commercial robberies.

Gang activity and high-rise public housing have been critical components to examining crime patterns in Chicago (Block 2000; Block and Block 1993; Smith 2014). Several of Chicago's high-rise public housing projects were notorious hot spots of crime, such as Cabrini-Green and the Robert Taylor Homes (Hunt 2009; Popkin et al. 2012; Smith 2014). Many of these projects were demolished after 2000 (although demolition of particular buildings in projects began earlier in the 1990s), and Popkin et al. (2012) attribute slight citywide declines in crime to such demolitions. However, Smith (2014), specifically examining gang-motivated homicides in Chicago from 1994 to 2005, suggests that public housing demolition *increased* the number of gang homicides. A possible reason, as detailed by Hagedorn and Rauch (2007), is that the demolition of large housing complexes and subsequent displacement of residents split up larger gangs into many smaller factions, resulting in higher levels of intra-gang violence (Papachristos 2013). More contemporary work by Bruhn (2018) using the same source data finds corroborating patterns to all of this work, with a slight increase of crime citywide post demolitions as well as spatial spillovers, but overall demolitions resulted in lower levels of crime.

For a final example, Block and Block (1995) show that some clusters of homicides are temporally proximate to clusters of liquor stores. Block and Block (1995) attribute this to how liquor stores can serve as informal congregation places, and because they need to consume the alcohol off-premises (as opposed to on-premise bars), individuals are more exposed to violence.

Preferably to examine the impacts of micro place characteristics on the spatial distribution of homicides, we would need measures of those micro place attributes over the entire study period – here 1965 through 2017. It is generally difficult to obtain historical measures of the micro places from such a long time ago. Thus we take a descriptive approach of identifying temporal trends in homicide and then ex ante attempt to identify whether spatial clustering of specific homicide trends correlate with other factors of the built environment.

Research on Crime Clustering

The contemporary focus on examining crime at micro places has also brought about research specifically aimed at *measuring crime clustering*. One of the initial articles, on the topic by Sherman et al. (1989) noted that a small number of addresses in Minneapolis accounted for the majority of calls for service. This is what later on prompted the attention to conducting hot spots policing (Braga et al. 2019; Sherman and Weisburd 1995).

This clustering of crime in a small minority of places is not only temporally consistent in one city over time (as previously discussed) but is also quite consistent from place to place. David Weisburd has described this as the law of crime concentration, in which around 5% of the micro places in a city account for around 50% of the crime (Weisburd 2015).

Weisburd's law is no doubt approximate – but has been verified in a wide variety of studies (Favarin 2018; Gill et al. 2017; Haberman et al. 2017; Lee et al. 2017). It has brought about several different pieces of research questioning the measurement and related aspects of Weisburd's law. Three of these aspects include the measurement of crime concentration when crime is rare, the randomness with respect to the clustering compared to typical Poisson (or other) processes, and the decomposition of clustering to more micro level units. A discussion of each follows.

Measuring Clustering When Crime Is Rare

A popular metric to measure clustering is the Gini index (Bernasco and Steenbeek 2017). One can imagine a curve in which the X-axis displays the proportion of an area under study, and the Y-axis displays the cumulative proportion of crimes (Spelman 1995). This graph presents a continuous analog to the observation that 5% of the area captures 50% of crime – one can select any place on the X-axis (e.g., 10% of the area) and see the corresponding proportion of crime captured on the Y-axis. The area *under* this curve has a direct relationship with the Gini index, so it is a popular measure to not rely on specific thresholds such as 5% of the area. Spelman (1995) shows that this Gini clustering tends to hold not only for spatial crime concentration but also for clustering in offenses and victimization. Eck et al. (2007) also examine the generality of such clustering across different crimes and in reference to other social phenomenon.

A potential issue that occurs with this metric though is that when crime is rare, it cannot by construction be entirely dispersed in the study area. Imagine one has 1000 spatial units, and only observed 500 crimes in the sample. Even if the crime was perfectly spread out in 500 unique locations, when estimating the Gini index, one would obtain a value of 0.5.

To account for this, Bernasco and Steenbeek (2017) suggested a modified Gini index, which in essence adjusts for the maximum number of areas crime could reasonably occur in. If G is the original Gini coefficient (which can be written in many different ways; see Allison, 1978 for one potential reference), the generalized Gini index can be written as:

$$G' = \max\left(n / c, 1\right) \cdot \left(G - 1\right) + 1$$

where n is the total number of crimes in the sample and c is the total number of spatial units. In the case that there are more crimes than spatial units, the adjusted Gini index is equal to the more usual formulation. When there are fewer crimes than spatial units however, the adjusted index will reduce the size of the original Gini index, and the domain of potential values is between 0 (no clustering) and 1 (perfect clustering). So in the example case listed, 500 crimes in 500 areas, one would obtain a Gini estimate of 0 (perfectly dispersed).

We note that another potential implication of crime counts is that because they are integer values, even if they are over the total number of the spatial units of analysis, it does not mean they can be equitably distributed in a perfect manner to achieve the *lowest* possible Gini value. For example, imagine you had 1000 areas and 1500 crimes. The *minimum* Gini one could have in this situation is 0.17 (500 areas with 1 crime, and 500 areas with 2 crimes). The adjusted Gini measure by Bernasco and Steenbeek (2017) does not take this into account.

In addition to this, the adjusted Gini approach by Bernasco and Steenbeek (2017) has also been criticized as inaccurate (Mohler et al. 2019). A main crux of the critique is that the adjusted Gini measure presumes places with 0 crimes are structurally zero – so should not count as places at all in the denominator portion of a crime clustering measure. When the number of crimes is much less than the number of areas, via simulations, Mohler et al. (2019) show that the modified Gini index can be badly biased toward 0. The solution to this problem is to then estimate the density of crime at locations. So even places with zero observed crimes ultimately contribute to the Gini measure.

This ultimately does not solve the problem with determining the correct measure though, which hinges on the identification of structural zeroes (locations which can never have a crime) vs observed zeroes (but have the possibility to observe a crime). For an extreme example, imagine one constructs an infinitely fine grid (and geotags the exact location of a crime event, down to the millimeter). One will likely never observe a homicide at the *exact* same location twice, and thus the Gini metric will always just be calculated based on a series of 1's and 0's. If one generates a finer grid of more 0's, the Gini index increases. Mohler et al. (2019) suggestion to estimate the density via a spatial Hawke's process can potentially eliminate some of this concern, but ultimately it still relies on the researcher distinguishing between grid cells that can potentially have crimes and eliminating those from the sample that can never be observed (say via the nature of the geocoding engine, or aspects of the built environment, or even the jurisdiction of the police department measuring the homicide locations).

Curiel et al. (2018) suggest an approach that uses latent class analysis to identify different mixtures of crime as the underlying measure. One can then use that estimate to generate the usual Gini statistic. Instead of using the observed crime counts, one uses the latent class estimate of the crime density and the proportion of observations that fall within that class. Then one can just replace those density estimates in the usual Gini formulation:

$$\frac{1}{2\,\Sigma_{i=1}^{k}\lambda_i q_i}\cdot\Sigma_{i=1}^{k}\Sigma_{j=1}^{k} q_i q_j \left|\lambda_i - \lambda_j\right|$$

In this formulation, there are k latent groups, and q_k is the proportion of the observations that fall within latent class k, and λ_k is the density estimate of homicides in that particular area. (Or more precisely q is the posterior mass for the entire group estimate.)

Because we are already using group-based trajectory models for the temporal analysis (e.g., Weisburd et al. 2004), this fits in directly with the latent class approach

Curiel suggests calculating the inequality of homicides over the time period. The trajectories provide an estimate of the latent classes and their density, which can then estimate the Gini metric from this measure *over time*. We note though that the suggestion of Mohler et al. (2019), to estimate the nonstructural zeroes via a negative binomial model, is likely reasonable as well. Given that group-based trajectory models often have little discrimination between the groups (Greenberg 2016; Skardhamar 2010; Wheeler et al. 2016), it may be more appropriate to measure such clustering over time via random effect negative binomial models (e.g., Braga et al. 2010a, b).

Our group-based trajectory estimates also however drop cases that experience zero homicides over the 53-year period (as they are trivially in a flat, 0 homicide trajectory). To justify our analysis of dropping these 0 homicide locations to our Gini (and also Theil) estimates, we can provide reasonable upper bounds on the possible density of locations that have experienced no homicides over the 53-year period for the 17,112 locations. For example, imagine if the true homicide density for a location was a Poisson distribution with a mean of only 0.00001 per year. In that case, the probability of observing 0 homicides within a year is $\exp(-0.00001) = p \gg 0.999$, for any *one* grid cell. The probability of observing all zeroes over the entire time period for all those locations is then $p^{53 \cdot 17112} \approx 0.0001$, or more simply $\exp(-0.00001 \cdot [53 \cdot 17112])$. As such, the average density over those areas experiencing zero homicides over the entire study period seems very unlikely to be *over* this value (but may of course be exceedingly much smaller).

This density value is exceedingly small – the density if a location experienced at least one homicide over the 53-year period would be $1/53 \approx 0.19$. Subsequently we feel justified in dropping these locations from subsequent clustering analysis. Although we can't say for certain that they will not experience a homicide in the future (no doubt some will), the probability is quite small and unlikely to greatly influence subsequent Gini or other clustering metrics when considering estimates over the entire time period.

Is the Clustering Random?

Initially in Sherman et al. (1989), to establish that the clustering of calls for service at particular locations was non-random, they conducted a goodness of fit statistic to establish that crimes were not Poisson distributed.

But even when rejecting the hypothesis that crimes are not distributed according to a Poisson distribution, that does not per se establish that the observed clustering is random or not. There have been two different approaches to studying this randomness; one is providing standard error bounds on the Gini metric (Bernasco and Steenbeek 2017; Mohler et al. 2019) or on specific crime concentration thresholds (Chalfin et al. 2020). The other is examining the temporal consistency of crime clustering using other various statistical techniques (Andresen et al. 2016; Levin et al. 2017; Hipp and Kim 2016; Vandeviver and Steenbeek 2019).

In terms of testing the rarity of crime, a common approach is to provide standard error estimates of the different metrics discussed. A common approach is to use the bootstrap, as the different metrics are difficult to derive analytical weights. Bernasco and Steenbeek (2017) use this to generate standard errors for the adjusted Gini (and it is a common approach for the unadjusted Gini). Chalfin et al. (2020) use this same bootstrap approach to generate standard errors for the proportion of areal units conditional on a particular crime threshold (e.g., to capture 50% of crime, it takes [1–6%] of the area in 95% of the bootstrap samples.

The second approach is aimed at the question of temporal consistency. Even if one identifies that 5% of the areas in a city capture 50% of the crime, this does not establish that it is the *same* 5% of places from year to year. Hipp and Kim (2016) address this by simply looking at the conditional relationships, the extent to which a crime occurs in the prior year it occurs in a future year. Levin conducts a simulation analysis, which shows that the 5% of areas threshold is often very arbitrary and that those locations tend to be quite volatile from year to year. Vandeviver and Steenbeek (2019) show that the *proportion* of crimes on street units tends to be quite volatile from year to year.

This would seem to be in contradiction to the prior analysis that established the long-term temporal consistency of crime at micro places (Andresen et al. 2016; Curman et al. 2015; Weisburd et al. 2004; Wheeler et al. 2016). However, it seems that these contradictions are more due to different methods of assessing temporal consistency than genuine paradoxical results. For example, the approach in Vandeviver and Steenbeek (2019) has subsequently been criticized as it fails to adjust for multiple comparisons, and the bootstrapping approach tends to be inaccurate when estimating extreme quantiles (Wheeler et al. 2019). And Levin's observation that many of the top 5% areas are volatile from year to year is a result of the arbitrariness of the 5% threshold. Many of the locations in his simulation where locations with only a few crimes and subsequently resulted in many ties for the top 5% threshold.

In this analysis, we provide descriptive statistics similar to those described in Hipp and Kim (2016) to establish whether homicides at micro places in Chicago show long-term temporal stability, as well as by using group-based trajectory models, one can identify long-term consistency of micro places, even when some places have local volatility in the total proportion of crime they capture from year to year.

Decomposing Clustering to the Appropriate Spatial Resolution

An implicit assumption in the prior analyses is the units of analysis under study. No matter what spatial unit of analysis one conducts the study under, it always begs the question of whether a different spatial unit of analysis would substantially alter the results, what is commonly referred to in geographic analysis the *modifiable areal unit problem*.

Several recent papers in criminology have attempted to reconcile this by examining typical inequality metrics at micro places, e.g., Lee and Eck (2019) and O'Brien

(2019), for example. Here we take a different tact and *decompose* the inequality metrics with within and between spatial variation using *Theil's* metric of inequality (Rey 2004). This technique is often used to examine the variation in income inequality; for example, it may be that regional variation explains different amounts of income, but *within* each region income is very uniform. One can ask the same question for homicides, although we clearly have neighborhood level variation in violence over time (Papachristos et al. 2018), are violent neighborhoods uniformly violent, or do they have pockets of high and low homicide areas. Prior research has identified that hot spots tend to be surrounded by low crime areas (Weisburd et al. 2004), but others have suggested general diffusion patterns (Wheeler et al. 2016). This measure provides an alternative metric by which to assess that question, beyond simply counting up hot spots (which themselves are highly arbitrary how you count them, Taylor 2015).

Theil's T measure of inequality can be written as:

$$T = \sum_{i=1}^{N} s_i \log\left(N s_i\right)$$

where N is the total sample size and i are indices for each spatial region. The term s_i then equals:

$$s_i = y_i / Y$$

where y_i is the total number of homicides in area i and Y is the total number of homicides in the entire sample. It happens that Theil's measure is directly related to measures of entropy, which were used by Lee and Eck (2019) to measure crime clustering at micro places. As such, for locations with zero homicides, we adapt the typical notation for entropy measures, in which case the term within the logarithm is undefined, but we treat its value as 0 (since the s_i term by which it is multiplied is obviously zero).

One can then decompose to a within and between component that sums to the total T inequality value:

$$T = \sum_{g=1}^{\omega} s_g \log\left(N / n_g s_g\right) + \sum_{g=1}^{\omega} s_g \sum_{i \in g} s_{i,g} \log\left(n_g s_{i,g}\right) +$$

Here n_g are the number of observations within each group, and s_g is the share of homicides for each group. In this formulation, the first portion (before the addition sign) is the between group component of Theil's inequality index, whereas the second term is the within component. One should then notice that the global Theil measure is a weighted average of the between group inequality (what one would estimate if you just calculated the global Theil for the aggregated areas) and a weighted average of the within Theil's indices for each area, with a higher weight for areas with more homicides.

We note here that similar to the problem in Bernasco and Steenbeek (2017), there is still an issue of indeterminacy when using Theil's index what counts for *N*. We use the same approach as for our Gini analysis – a location counts in the final tally for *N* if it had at least one homicide over the entire sample period. Places with zero homicides over the entire period are not counted toward *N* for the Theil analysis.

Identifying Specific Spatial Clusters

In addition to the global clustering metrics (Gini' and Theil's measures), a potential alternative approach in place of measuring the *overall* clustering of crimes in a particular global metric is to identify specific spatial clusters of crime (Block and Block 1995; Block 2000; Haberman et al. 2017). These are useful for descriptive analysis. Here we use two different approaches to identify specific locations of space and time clusters of one hot spot. One is a metric based on kernel density estimation, the highest density region (Hyndman 1996). The second is a space-time clustering metric referred to as SaTScan (Zeoli et al. 2014).

To visually examine the crime concentration over the time period, we estimate kernel density maps at 5-year intervals using a 750 m bandwidth (the same as that used in Block 2000) and display the highest density region (Hyndman 1996). This provides a visual analog to the typical Lorenz curve and allows one to illustrate on the map the approximate area that contains 50% of the homicides in the given time period in Chicago. To describe how this is calculated, Fig. 2.1 displays a diagram of a simplified 3 by 3 grid which represents a hypothetical kernel density estimate in grid A. One then identifies the density of the entire grid, 12 in this example, and arbitrarily sets how much of that density one wants to capture, here 50%. This corresponds to a total density of over 6 in this example. One then turns the original kernel density into a cumulative kernel density estimate, grid B, and identifies the region that captures at least 50% of the density, in this example the cumulative density just above a value of 6, shown with a light grey background. This mapped area will represent a greater area than the micro level grid cells, as the kernel density estimate smooths out homicides over a greater area. But, it provides more visual stability to examine changes in homicide patterns from year to year.

A

0	0	0
1	1	1
2	3	4

B

12	12	12
12	11	10
9	7	4

Fig. 2.1 Diagram depicting how the highest density region is defined. If the grid cells on the left (A) are the original kernel density estimate, which sum to a total density of 12, then to capture 50% of the density, one would need to draw a contour around an area that has a cumulative density of over 6. The grid cells on the right then depict transforming the kernel density into a cumulative kernel density and then identifying the cells that capture over 50% of the density in the lower right corner, highlighted with a gray background

To display how such clusters change over time, we estimate the highest density region over 5-year temporal slices of the data and use maps to illustrate how they change. Another direct approach of identifying space-time clusters however is to use a spatiotemporal scan statistic, SaTScan. SaTScan was originally developed by epidemiologists to identify spatial and temporal clusters of disease outbreaks (Kulldorff et al. 1998). It can be applied similarly to crime data though as well (e.g., Zeoli et al. 2014).

Here we conduct a retrospective space-time scan statistic using the grid cell locations with at least one homicide over the entire time period and incorporate yearly data at the grid cell level. We do not include population estimates into the clustering routine and simply give each grid cell a population estimate of 1 for each grid cell year. We specify the space-time search radius to be circular and 5 years and 5000 m. We further restrict the reported clusters to those that achieve statistical significance via a p-value of under 0.05 and incorporate more than one location (so that one even with multiple homicides does not result in a cluster). This is accomplished by conducting 999 Monte Carlo simulations under a pattern of space-time randomness. We use the SaTScan software to ultimately identify nine space-time clusters based on the homicide data in Chicago.

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Chapter 3
Understanding the Data

Abstract This chapter describes in detail the Chicago homicide data that were used to conduct this study, as well as how the data was geocoded and aggregated to grid cells for spatial data analysis. The Chicago homicide data is emphasized in terms of domestic vs non-domestic homicides, which provides a useful framework for understanding some of the variations of violence at micro places. The chapter concludes with a description of the geographic levels of analysis that were used, including how and why the 150 m cells were selected as the primary unit of analysis.

Keywords Chicago Homicide Dataset · Domestic homicide · Non-domestic homicide · Grid cell · Street segment · Chicago Crime Commission

The homicide data for this analysis comes from two sources, homicides from 1965 through 2000 come from the Chicago Homicide Dataset (Block 1997; Block and Block 2011). While the publicly available Chicago Homicide dataset (available via ICPSR) only includes homicides from 1965 through 1995, and only has a geographic specificity at the level of census tracts, here we use the original dataset that is not publicly available, which has homicide incidents geocoded to the address level and has extended homicides until the year 2000. This includes a total of 27,285 homicides over the 36-year period.[1] More recent homicides from 2001 to the present are publicly available from the Chicago Open data portal, https://data.cityofchicago.org/. This dataset we have compiled includes a total of 8891 homicides from 2001 through 2017. Each dataset contains individual homicides (one incident can result in multiple homicides) and so combining the two results in a total of 36,176 homicides over the 53-year period. Table 3.1 displays some aggregate statistics detailing the source and total values of the homicide data.

[1] The CHD begins with 1965 homicides because it was the last year of a period with relatively few homicides. Here we use the year the injury occurred for the historical homicide dataset. This results in three cases being dropped in which the incident occurred in 1964. The contemporary homicide dataset uses the date the incident was reported.

A. P. Wheeler et al., *Micro-Place Homicide Patterns in Chicago*, SpringerBriefs in Criminology, https://doi.org/10.1007/978-3-030-61446-1_3

The datasets differ in their original source; while the homicides in the historical Chicago Homicide dataset were coded from information directly in detective reports, the contemporary Chicago homicides are taken from incident reports. For each, the location of the incident is recorded as where the body was found, not necessarily where the homicide originally occurred. For the contemporary Chicago homicide dataset, all crime incidents disseminated by the Chicago PD are truncated to the 100 block (e.g., 12XX W Madison St.) in order to preserve some privacy for the victims. These incidents are then automatically geocoded to latitude and longitude coordinates. The historical Chicago homicide dataset were geocoded automatically and then by hand by students, as automated procedures using Census TIGER files resulted in an unacceptable level of missing incidents (Block 1995). Where available, homicides were geocoded to the nearest address, but some homicides could occur in areas with no relevant nearby address, such as a body recovered in the Chicago river. In these instances, homicides were manually assigned to the approximate location based on information in the homicide report. For both the historical homicides and the contemporary homicides, the geocoding hit rate is close to 100%.

Figure 3.1 displays the yearly number of homicides over the entire time period for the combined dataset. One can see from this graph the crime drop period, start-

Table 3.1 Total homicides per dataset

Source	Year range	Total homicides
CHD	1965–2000	27,285
Open data	2001–2017	8,891
Total	1965–2017	36,176

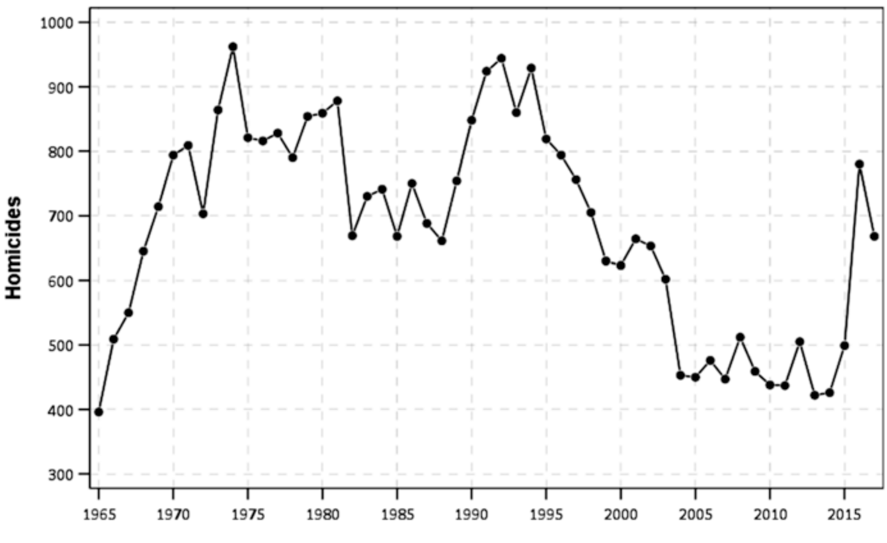

Fig. 3.1 Homicides per year in Chicago, 1965 through 2017

ing in Chicago in the early 1990s, levelling off in the mid-2000s, and the dramatic increase in homicides in 2016. The year 2017 then subsequently decline someone, but was still a high number relative to the number of homicides before the uptick in the early 2010s. The dramatic increase in 2016 is still not as large in magnitude of the number of homicides in Chicago either in the 1970s nor the early 1990s.

Figure 3.2 displays a breakdown of the homicides between domestic related incidents and all other homicide incidents. While we do not have breakdowns identifying whether contemporary homicides appear related to gang violence, we do have a marker in both datasets that distinguish whether a homicide is related to a domestic (e.g., the perpetrator was a significant other or a family member of the murdered individual). Figure 3.2 shows that the year to year volatility of homicides appears entirely driven by the non-domestic category. Domestic homicides appear to have a linear decrease over the entire time period, going from near 100 to now only 50 per year.

The spatial unit of analysis used in this study are a set of regular grid cells of 150 by 150 m in size over the entire city. While much of the recent literature on crime at micro places uses street segments (e.g., Schnell et al. 2016) or census blocks (Bernasco and Block 2010), we do not use such units given our data sources for several reasons. The first reason is that 100 blocks do not easily define street segments in Chicago. For one example, the street segment encompassing Ashland Ave. between Diversey and Wrightwood spans from 2600 to 2750. Additionally, many street segments have the opposite pattern; a street segment only contains half of the typical 100 block of addresses. This would not be a problem if Chicago released individual address level data with crime incidents, but incidents are only given at the level of specificity of 100 blocks. This makes it impossible in some instances to

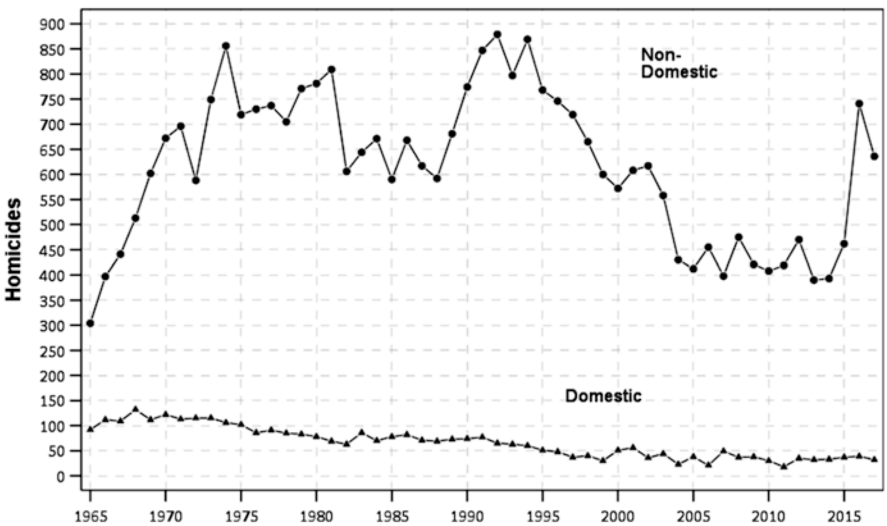

Fig. 3.2 Homicides per year in Chicago, broken down by domestic vs non-domestic homicides

properly aggregate the crime incidents to a consistent set of street segments. Additionally, truncating to the 100 block does not displace the homicide to a specific side of the street, and this is necessary if one wants to assign a crime location to a particular census geography (as the borders of census geographies are defined by the streets). As a result, truncating to the 100 block prevents a researcher from analyzing crime at the micro place unit of census blocks.

The second reason is that the historical Chicago Homicide Dataset was geocoded using a different street file than the contemporary Chicago homicide dataset. Changes in streets over time make it difficult to identify exact repeats over time (Block and Block 1995).

For these two reasons, we chose to use small grid cells as our spatial unit of analysis. The size of 150 m is specifically chosen as it represents a size similar to the typical length of a street segment in Chicago and has been used in prior analysis of Chicago gang activity (Block 2000). Using a set of regular grid cells allowed us to aggregate the two datasets without needing to worry about rectifying slightly displaced streets from the historical data. While this does not guarantee that one street in the historical data could be displaced to a different grid cell, we examined various time series graphs and changes between the two datasets. We found no instances of large discontinuities from 2000 to 2001. Although we will show several places that have either decreased or increased over the time period, there were no examples where a high homicide grid cell moved one block over, which could be a result of inconsistent geocoding definitions between the two datasets. There is a total of 27,453 grid cells in the analysis, of which 10,361 contained at least one homicide over the 53-year period.

Figure 3.3 displays those grid cells and the *cumulative* number of homicides occurring in those grid cells over the entire time period under study. Superimposed on the map are neighborhood boundaries, known as Community Areas in Chicago. From this map one can easily see several widespread clusters of homicides in both the west and south portions of Chicago. Several micro place patterns though emerge as well, such as a run up the Gold Coast in the north, a run along the historical black belt, and a cut out area in the south east that is the Hyde Park, the area around the University of Chicago.

In addition to homicides, we incorporate several additional datasets to superimpose on maps in the study. We map the location of high-rise public housing locations, as well as the location of reported gang territories. A shapefile of the building grounds for high rises built from 1938 to 1968 was obtained from Dennis McClendon, who used various historical sources to digitize the original grounds (McClendon 2005). Gang territories were taken from a public map listed by the Chicago news site WBEZ (Ramos 2012), which were digitized based off of 2010 data published in the 2011 *Gang Book*, published by the Chicago Crime Commission. As illustrated in the prior map, we also have downloaded a map of 77 Chicago community areas, in which we decompose historical Theil indices to between and within homicide clustering in neighborhoods.

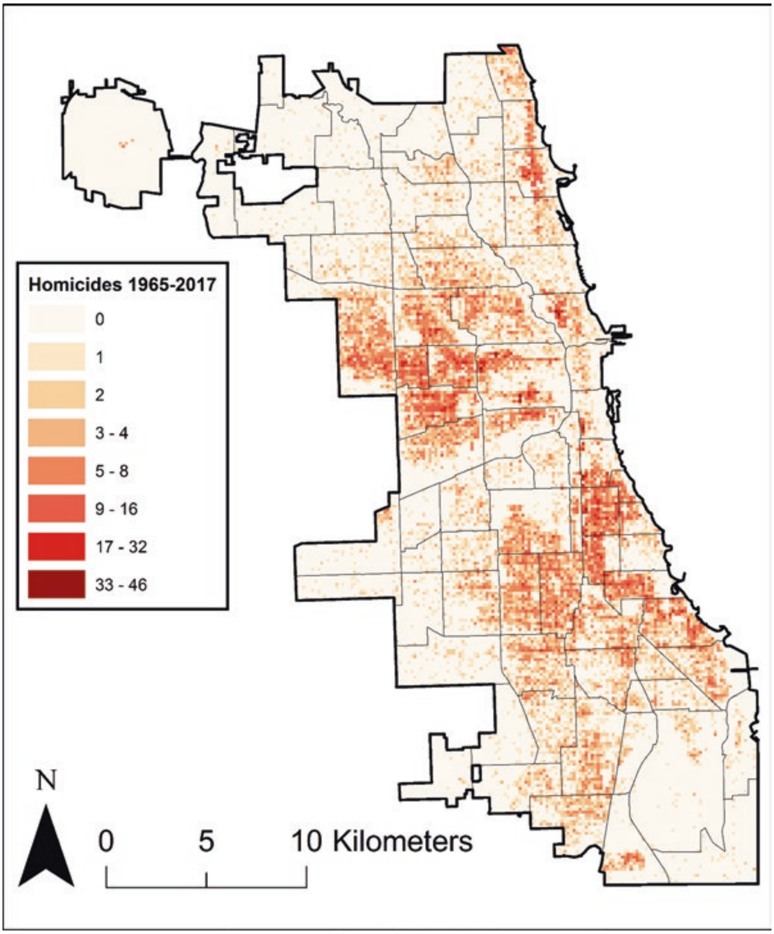

Fig. 3.3 Count of homicides in 150 meter by 150 meter grid cells in Chicago, 1965 through 2017. Lighter gray lines represent community areas

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Chapter 4
Research Questions and Methods

Abstract This chapter examines the three primary research questions: (1) Do homicides cluster in space and time? (2) Do micro places show spatiotemporal consistency or instability over the 53-year study period? and (3) Are the recent Chicago homicide spikes occurring in the historical high-homicide places, or are these new homicide problems in new places? The chapter explains how various spatiotemporal approaches were conducted to answer the three research questions. These spatiotemporal analyses included global clustering (using generalized Gini indexes), cluster analysis using Theil indexes, SaTScan spatial and temporal clustering, and traditional kernel density mapping.

Keywords Geographical clustering · Micro places · Theil index · Gini index · Global clustering · Transition probabilities · Growth mixture models · Zero-inflated Poisson models · Longitudinal homicide patterns

Given the prior analyses on crime trends at micro places over long temporal periods, we have generated several different specific research questions which guide our overall analyses:

Question 1: Do homicides show geographical clustering? And is that clustering temporally consistent over the entire 53 years? Additionally, are homicides more or less clustered during high homicide years? And is that clustering attributable to simply neighborhood level differences?

Question 2: Do micro places show historical consistency or volatility in homicides from year to year? Also do micro places that have homicides follow unique temporal trajectories? If they do, what are the spatial distributions of those trajectories?

Question 3: Are the recent increases in homicides in Chicago in 2017 concentrated among micro places that had historically high homicide rates, or is the recent increase attributable to places that are not historical hot spots of homicides?

A. P. Wheeler et al., *Micro-Place Homicide Patterns in Chicago*, SpringerBriefs in Criminology, https://doi.org/10.1007/978-3-030-61446-1_4

To answer question 1, we use several different approaches. One approach is measuring global clustering via the generalized Gini index proposed in Bernasco and Steenbeek (2016) that takes into account when there are fewer crimes than geographical units, as is the case when examining temporal windows in Chicago that are smaller than the entire 53-year period.

A second approach we use is breaking down the clustering into within and between neighborhood clustering using the Theil index. Finally, using latent classes identified via group-based trajectory modeling, we also incorporate the clustering formula based on the latent crime density estimate described by Curiel et al. (2018). (Formulas for these metrics were given in the prior literature review section.)

In addition to global clustering metrics, we also examine specific spatial and temporal clusters, via highest density regions estimated via kernel density, as well as SaTScan spatial and temporal clusters. As opposed to a single number, these techniques return a map and specific areas that have experienced a high density of homicides.

These techniques, however, are not suitable to assess micro-level temporal stability, our research question number 2. The kernel density maps could either smooth over volatility from place to place over the time period or be the result of temporal consistency of micro places. It cannot distinguish between those two processes. Similarly, showing that the top 5% of places accounts for the top 50% of crime does not indicate that it is the same specific micro places from time period to time period (Hipp and Kim 2016; Levin et al. 2017). To better assess long-term temporal patterns (question two), we conduct two different analyses.

First, we estimate transition probabilities to show the probability a homicide occurs in a grid cell conditional on a homicide occurring in a grid cell at a prior time period (Hipp and Kim 2016). For a simple example, imagine a particular year had 500 grid cells with a homicide. In the following year, we identify that 50 out of those 500 original grid cells had a homicide, 10%. This represents the transition probability of $P(\text{Homicide}_{t1} \mid \text{Homicide}_{t0})$. We then show graphs illustrating those transition probabilities over multiple years.

For a second analyses to assess long-term historical consistency, we fit growth mixture models to identify temporal clusters of differing trajectories (Nagin 2005). We fit zero-inflated Poisson regression models using the Stata *traj* plug-in (Jones and Nagin 2013). The zero-inflated Poisson model is easiest to understand when written in two parts, the zero-inflation part and the Poisson regression part, although when estimating the model, each part is fit simultaneously. For simplicity, we fit only a single parameter for the zero-inflation part for all micro place units over the entire time period, and we denote this zero inflation probability as π.[1] The mixture model for the Poisson part can be written as:

[1] Models that allowed the zero-inflation parameter to vary as a cubic polynomial for time for each mixture component slightly improved model fit compared to models with an equal number of mixture components, but resulted in nearly equivalent temporal trajectories in terms of levels and trends over time. For this reason we only report the solutions that assume a constant zero-inflation for all units over the entire time period.

$$\lambda_{it}^{k} = \beta_0^k + \beta_1^k\left(t\right) + \beta_2^k\left(t^2\right) + \beta_3^k\left(t^3\right)$$

where the predicted value at micro place i and year t is a cubic polynomial function of time. Time is coded as 1 through 53, with year 1965 equal to 1. A cubic function is chosen a priori as the long time period may invite more complicated functions. The k superscripts then denote different solutions for the mixture groups, and each observation is given a posterior probability estimate as to which equation it most likely resembles. The final expected number of homicides at a micro place grid cell for any year is then:

$$\left(1-\pi\right)\sum_{k=1} p_k \cdot \exp\left(\lambda_{it}^{k}\right) = \mathbb{E}\left(\text{Homicides}_{it}\right)$$

where p_k is the posterior probability an observation belongs to that mixture equation. This is used as a weight in calculating the final expected number of homicides at a micro place grid cell. Summing those values over the k mixture groups, and then multiplying by the complement of the zero-inflation parameter (the probability a grid cell will have 1 or more homicides), provides the expected number of homicides at a particular grid cell for a particular year.

To choose the final number of mixture groups, we rely on several different summaries, as well as qualitatively evaluating the final produced trajectories. While we report the BIC statistic, which is often used for relative model selection, with many observations and longer time periods, it tends to select an excessive number of groups (Erosheva et al. 2014). Thus we also examine the average posterior probability for each group assignment and the odds of correct classification (Nagin 2005), and we also visually examine the resulting trajectories. We examine model solutions for 2 through 11 groups. We stopped at examining 11 groups as models with more components produced warnings of singular variance-covariance matrices for the parameter estimates, as well as the fact that the 11th group solution produced an explosive trajectory.

For this analysis, only grid cells that experienced at least one homicide over the entire study period were used (n = 10,361) as those observations not experiencing at least one homicide are trivially in a flat, zero homicide trajectory (as we are not using any other information to predict the trajectory path over time).

We assign each grid cell to the mixture group that has the highest posterior probability and then map the different trajectories. In addition to the maps of trajectories, we superimpose former high-rise public housing projects, as well as maps of gang territories to visually determine the extent to which the trajectories are spatially nearby each potential source.

We use portions of each prior analysis to help us address research question 3: Are the homicide increases in 2016 and 2017 consistent with prior geographic homicide patterns, or do they illustrate new patterns? We use time series graphs of the trajectory groups to answer if the recent homicide increases in Chicago in 2016 and 2017 are concentrated among a few places and whether that concentration is limited to places with historically high homicide prevalence, or if it has spread to new locations that have not before seen high numbers of homicides nearby. We use the Gini clustering metric to attribute whether homicides appear to be more clustered in recent years, or whether they appear to be spreading out in a wider area. And finally we examine specific space-time clusters using SaTScan to identify if any specific, local space-time clusters appear in the data. All three of these techniques in concert will help us address this particular research question.

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Chapter 5
Analysis and Results

Abstract This chapter details the results of the multiple analyses conducted in the previous chapter, how the research questions were answered, and comprehensive explanations of each of the results, tables, and incorporated illustrations. This includes detailed statistics for each of the 77 Chicago community areas, as well as group-based trajectory analysis which suggests that homicide consistency in Chicago community areas is not the norm.

Keywords Gini crime clustering · Empirical cumulative distribution function · Chicago community area · Theil's inequality index · Group-based trajectory analysis · Homicide spike · Homicide dispersion · Public housing · Gang territories · Kernel density mapping · Homicide hot spots · SaTScan clustering · Chicago community areas

Gini Crime Clustering

To answer our first research question, the extent to which homicides cluster, we undertake two analyses. One is the measure of crime clustering over time via the Gini and the generalized Gini coefficient. The second is to decompose the level of the clustering and see the extent to which clustering occurs at the neighborhood community area level, or at the micro place grid cell level.

Figure 5.1 displays the empirical cumulative distribution function (ECDF) for all 36,176 homicides within the 27,473 grid cells over the entire period. One hundred percent of the homicides occurred in 10,262 cells (37%). Therefore, the remainder of Fig. 3.3 is flat at 100%. Figure 3.3 approximately conforms to Weisburd's (2015) law of crime concentration, with 5% of the grid cells accounting for just under 45% of the homicides in Chicago. The Gini coefficient, which higher values indicate more inequality (and has a range of 0–1)[1] for this particular ECDF, is 0.8.

[1] With finite populations the upper bound of the Gini coefficient is $1 - 1/n$ (Allison (1978), where n is the total number of units in the sample. Even when considering the generalized Gini coefficient, this only reduces the upper bound by a maximum of 1/396 (the reciprocal of the number of homicides in 1965, the year with the fewest homicides in the sample) – less than 3 hundredths – in this sample.

A. P. Wheeler et al., *Micro-Place Homicide Patterns in Chicago*, SpringerBriefs in Criminology, https://doi.org/10.1007/978-3-030-61446-1_5

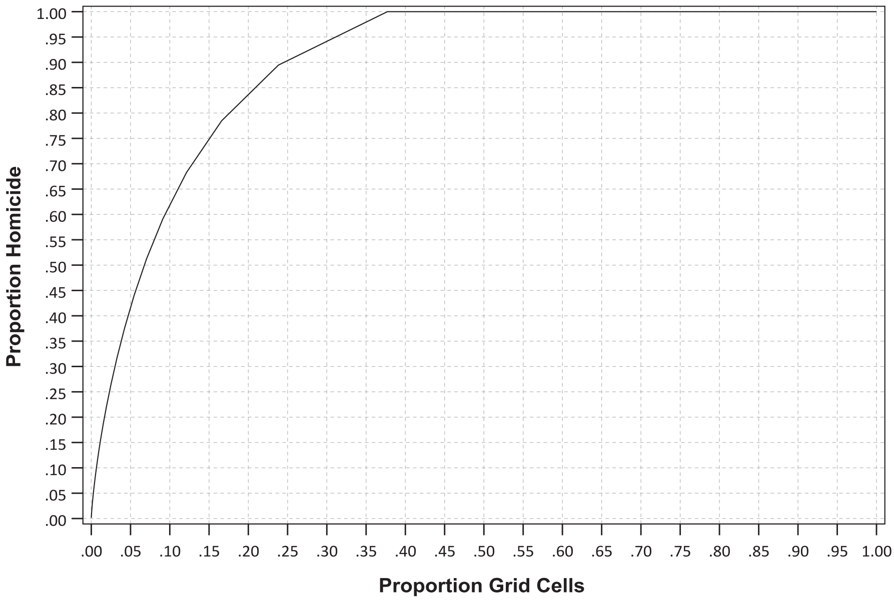

Fig. 5.1 Empirical cumulative distribution function (ECDF) for 36,176 homicides within 27,473 grid cells in Chicago. 5% of the grid cells contain just under 45% of the homicides. This ECDF corresponds to a Gini index of 0.8

However, such a calculation only works when examining crime counts that are larger than the total number of spatial units. When restricting such a calculation to homicides in any particular year, no more than 3.5% of the grid cells will include 100% of the homicides, as there is a maximum of 963 homicides in any year. To account for this, we use the generalized Gini index proposed by Bernasco and Steenbeek (2016), and Table 5.1 displays that index for homicides aggregated to 5-year periods, with the exception of the latest period that is only 3 years (2015, 2016, and 2017). This table shows that while the original Gini index shows homicides are incredibly clustered with Gini values of above 0.9, this is an artifact of so few homicides per year. The generalized Gini index has much lower values for each 5-year period. Additionally, the generalized Gini shows a temporal trend, with higher generalized Gini values of 0.5 earlier in the series and currently generalized Gini values of less than 0.4.

One should be wary of interpreting the generalized Gini metric for the latest 2015–2017 set though with only 2 years, as selecting different yearly subsets substantially changes the estimate. For example, estimating the generalized Gini index on a yearly basis for homicides further reduces the Gini coefficient to between 0.1 and under 0.3. Figure 5.2 displays a scatterplot of the yearly generalized Gini index on the Y-axis and the total number of homicides on the X-axis. The points are colored, so earlier years are black, and later years turn into brighter red. This shows a positive correlation between the total number of homicides and the generalized

Table 5.1 Gini and generalized Gini indices for 5-year periods

Year range	Gini	Generalized Gini	Total homicides
1965–1969	0.95	0.53	2814
1970–1974	0.93	0.53	4132
1975–1979	0.93	0.52	4109
1980–1984	0.93	0.48	3877
1985–1989	0.93	0.44	3521
1990–1994	0.92	0.48	4505
1995–1999	0.92	0.42	3704
2000–2004	0.93	0.37	2995
2005–2009	0.95	0.36	2344
2010–2014	0.95	0.36	2228
2015–2017	0.96	0.37	1947

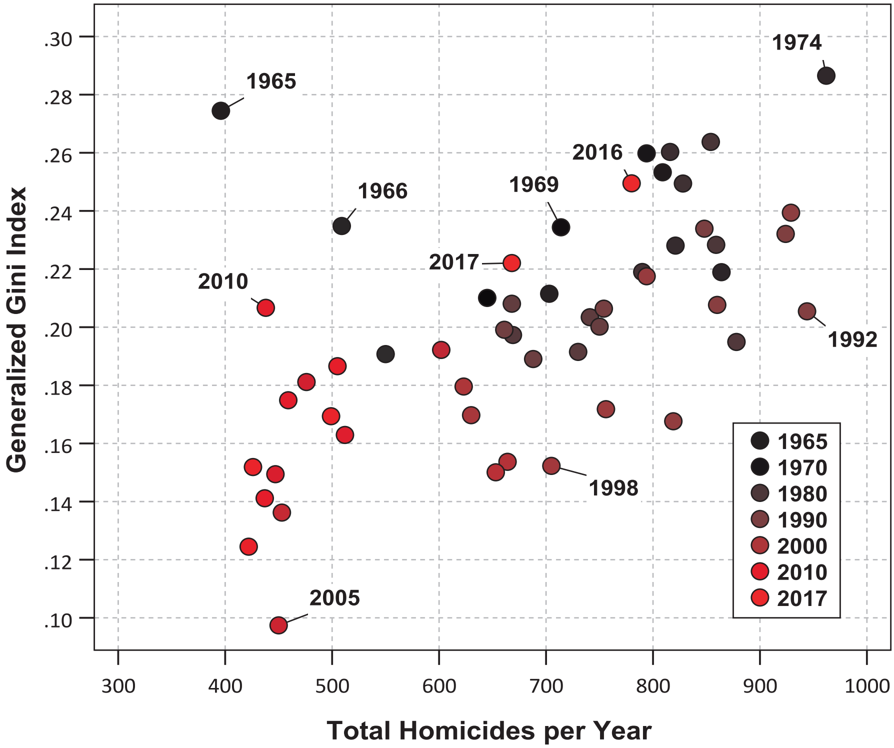

Fig. 5.2 Scatterplot between generalized Gini index and homicides per year. The overall correlation is 0.59. The color ramp for the points is continuous – earlier years are black, and they gradually change to red for more recent years

Gini coefficient in this sample (with a Pearson's correlation of 0.6). While 1965 bucks the trend, with fewer homicides but a larger generalized Gini estimate, most of the earlier years with more homicides in the 1970s showed more clustering, whereas later years in the 2000s showed less clustering. The homicide uptick in 2016 migrated back to a higher generalized Gini value. The evidence presented here suggests that years with more homicides tend to be more spatially clustered than during years with fewer homicides (according to the generalized Gini coefficient). This however is not dispositive that there is temporal consistency in the places with many homicides over time.

Theil Decomposition of Within vs Between Neighborhood Clustering

The prior analysis examined clustering of homicides over time. Another question one may ask – given the historical focus of crime on neighborhood patterns in Chicago (and in criminology in general) – is that: Are such clusters simply the result of long documented, historical neighborhood differences in crime? Is there any utility in examining such trees, when the forest of neighborhood crime inequality is what entirely explains such homicide clustering patterns over time?

To address this question, we leverage a different clustering metric, Theil's inequality index, and decompose the total amount of clustering to within community areas and between community areas in Chicago. For this analysis we use the homicide trends over the entire 53-year period, but aggregated to grid cells. We also discard any grid cells that had zero homicides over the entire time period, so the minimum number of homicides is equal to 1. Cells with 0 values are technically undefined in Theil's analysis, as it requires taking the log of 0.

For the entire 53-year period, Theil's analysis reveals that the overall level of clustering is 0.39. Values closer to zero are less clustered (if all homicides never repeated in the same grid cell, Theil's value would be 0). Maximum Theil's value is equal to the natural logarithm of the total number of grid cells, here $\ln(10{,}361) \approx 9.25$, so the overall amount of clustering is quite low over the entire time period according to this metric. (Using all grid cells for the denominator for this metric results in a slightly higher Theil index of over 1, but it is still quite small compared to maximum inequality.)

Again, we leverage Theil's inequality metric as it affords us the opportunity to do a breakdown of the metric to *within* neighborhood inequality in homicides vs *between* neighborhood inequality. For a simplified example of the difference, imagine a city in which half of 1000 grid cells had an average of 1 homicide per 50 years and the other half have 10 homicides. This results in a Theil's measure of inequality of 0.39 (same as that observed).

But now also imagine a scenario in which the two types of areas are determined by being in neighborhood A (the low homicide neighborhood), or neighborhood B (the high homicide neighborhood). If one did a breakdown of Theil index *within* each neighborhood, it results in entirely no inequality. In this scenario the entire global inequality metric of 0.39 is determined by between neighborhood differences.

The opposite scenario would be if the high and low homicide locations are randomly dispersed. In that case, the between neighborhood inequality would be near 0, but the within neighborhood inequality would be approximately equal to the global pattern.

Conducting this breakdown for the Chicago homicide data at the community area level, it results in the *between* neighborhood inequality for Theil index as equal to 0.11, so around 28% of the homicide inequality is due to between neighborhood differences. This still suggests that quite a large portion of homicide clustering occurs within neighborhoods, even when those neighborhoods are low or high crime.

Figure 5.3 displays the local Theil index breakdown for each of the 77 community areas (on the Y-axis) and the average number of homicides per grid cell on the X-axis. Because we eliminated grid cells with no homicides over the entire time period, the minimum average homicide has to be at least 1. This would correspond to a neighborhood in which every grid cell in the sample *only* had one homicide. This indicates no repeats of homicide over time and an entirely dispersed pattern. This does occur in one neighborhood in Chicago – Edison Park. Edison Park had

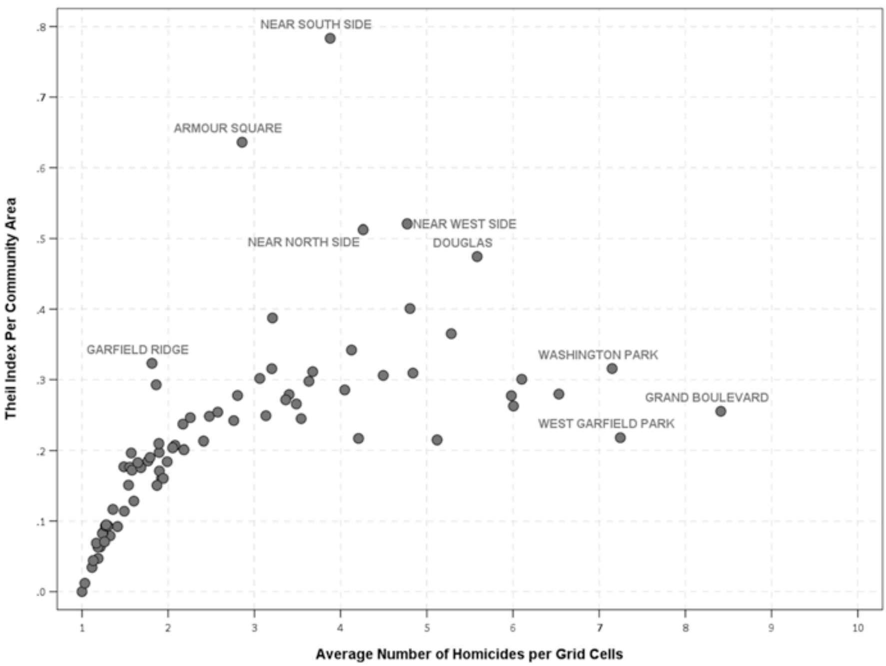

Fig. 5.3 Scatterplot between the local Theil metric for Chicago community areas and the average number of homicides per grid cell (for only grid cells with at least one homicide over the 53-year period)

only five homicides over the entire time period, and those five homicides were located in unique grid cells.

The community area that displayed the most homicide clustering was not the area with the highest average number of homicides per grid cell; it was the Near South Side. Several of the locations with higher average homicides appear to have less homicide inequality, such as Grand Boulevard, West Garfield Park, and Washington Park. This suggests these locations have much more clustered homicides in several grid cells, despite having a large number of homicides over the years. As such, they appear to be better candidates to look for long-term temporal consistency in homicides, whereas places like Near North Side and Near West Side may show more sporadic homicide trends.

Table 5.2 displays the Theil breakdown per individual community area, the total number of homicides observed over the 53-year period, and the total grid cells that experienced at least one homicide over the time period. The table is ordered in descending order by the highest Theil index neighborhoods. And Fig. 5.4 displays a map of the Theil index per community area. From the map one can see that the areas of the highest clustering of homicides tend to be near the smaller community areas near the inner loop of the city. The larger neighborhoods toward the periphery of the city tend to have lower Theil index values. This suggests there still may be a modifiable area unit problem with examining this clustering metric and that it results in more clustered values for locations with fewer grid cells overall.

Transition Probabilities to Examine Homicide Patterns over Time

Migrating back to analysis of homicide trends over time – neither prior analysis of Gini nor Theil clustering directly addresses the question of temporal persistence. For the Gini analysis over time, homicides could be clustered *within* any particular time period, but randomly change from time period to time period, and the statistic would be unable to decipher such a pattern. Additionally, Theil's analyses aggregated over the entire time period. As such, the Theil patterns could be attributable to single homicide incidents in which multiple homicides occur at once, they need not signal a place is a consistently high homicide location over the 53-year period.

As a simplified test to demonstrate the historical predictability of homicide patterns in these micro place grid cells over time, we examine the probability that a homicide in 1 year occurs in a grid cell that had a homicide in the prior year (Hipp and Kim 2016). For instance, based on the 453 grid cells that had at least one homicide in 2015, 70 of those cells also had a homicide in 2016, 15%. Replicating this 1-year transition probability estimate for all prior years in the sample, the overall probability of homicide consistency is 13%. If one were comparing to just guessing whether any particular cell would have a homicide, assuming total geographic dispersion for the year with the most homicides in the sample (1974 with 963 homicides) would result in only 3.5% of the grid cells having a homicide. Thus, knowing

Table 5.2 Theil index breakdown per community area

Community area	Local Theil index	Neighborhood mean	Total homicides	Total grid cells
Near South Side	0.78	3.9	225	58
Armour Square	0.64	2.9	120	42
Near West Side	0.52	4.8	1742	365
Near North Side	0.51	4.3	733	172
Douglas	0.47	5.6	631	113
Kenwood	0.40	4.8	394	82
Edgewater	0.39	3.2	321	100
Uptown	0.37	5.3	782	148
Lower West Side	0.34	4.1	652	158
Garfield Ridge	0.32	1.8	125	69
Washington Park	0.32	7.2	1001	140
Riverdale	0.32	3.2	285	89
Greater Grand Crossing	0.31	3.7	1022	278
South Shore	0.31	4.8	1263	261
Humboldt Park	0.31	4.5	1308	291
Chatham	0.30	3.1	582	190
North Lawndale	0.30	6.1	1745	286
Fuller Park	0.30	3.6	178	49
Lincoln Park	0.29	1.9	294	158
Austin	0.29	4.0	2194	542
Oakland	0.28	6.5	307	47
South Chicago	0.28	3.4	718	211
Rogers Park	0.28	2.8	359	128
Woodlawn	0.28	6.0	945	158
West Town	0.27	3.4	1224	364
New City	0.27	3.5	924	265
East Garfield Park	0.26	6.0	1135	189
Grand Boulevard	0.26	8.4	1556	185
Logan Square	0.25	2.6	698	271
Auburn Gresham	0.25	3.1	959	306
Chicago Lawn	0.25	2.5	493	199
Lake View	0.25	2.3	431	191
South Lawndale	0.24	3.5	921	260
Roseland	0.24	2.8	969	351
Hyde Park	0.24	2.2	152	70
West Garfield Park	0.22	7.2	1036	143
West Englewood	0.22	4.2	1254	298
Englewood	0.21	5.1	1669	326
West Pullman	0.21	2.4	564	234
Morgan Park	0.21	1.9	227	120
Albany Park	0.21	2.1	212	102

(continued)

Table 5.2 (continued)

Community area	Local Theil index	Neighborhood mean	Total homicides	Total grid cells
Avalon Park	0.20	2.1	158	77
Washington Heights	0.20	2.2	393	180
Calumet Heights	0.20	1.9	163	86
East Side	0.20	1.6	77	49
O'Hare	0.19	1.8	34	19
Gage Park	0.19	1.8	226	128
Loop	0.18	2.0	167	84
South Deering	0.18	1.6	206	125
Irving Park	0.18	1.5	159	107
Lincoln Square	0.18	1.6	129	83
Pullman	0.18	1.7	101	60
McKinley Park	0.17	1.6	79	50
Brighton Park	0.17	1.9	241	127
Avondale	0.16	1.9	200	104
Burnside	0.16	1.9	68	35
North Center	0.15	1.5	97	63
Hermosa	0.15	1.9	129	69
Bridgeport	0.13	1.6	141	88
West Lawn	0.12	1.4	53	39
Belmont Cragin	0.11	1.5	234	157
West Elsdon	0.09	1.3	41	32
Mount Greenwood	0.09	1.3	14	11
North Park	0.09	1.3	39	30
Archer Heights	0.09	1.4	48	34
Clearing	0.08	1.2	46	37
Dunning	0.08	1.2	47	38
Ashburn	0.08	1.3	118	89
West Ridge	0.07	1.3	101	80
Montclare	0.07	1.2	21	18
Hegewisch	0.06	1.2	40	33
Jefferson Park	0.06	1.2	32	27
Forest Glen	0.05	1.2	19	16
Portage Park	0.04	1.1	78	69
Beverly	0.03	1.1	48	43
Norwood Park	0.01	1.0	31	30
Edison Park	0.00	1.0	5	5

where prior homicides occurred appears to provide a much better guess as to whether a homicide will occur there in the future than random. This holds true over longer historical patterns as well. For the 335 grid cells that a homicide occurred in 1965, 8% of those grid cells contained a homicide in 2016.

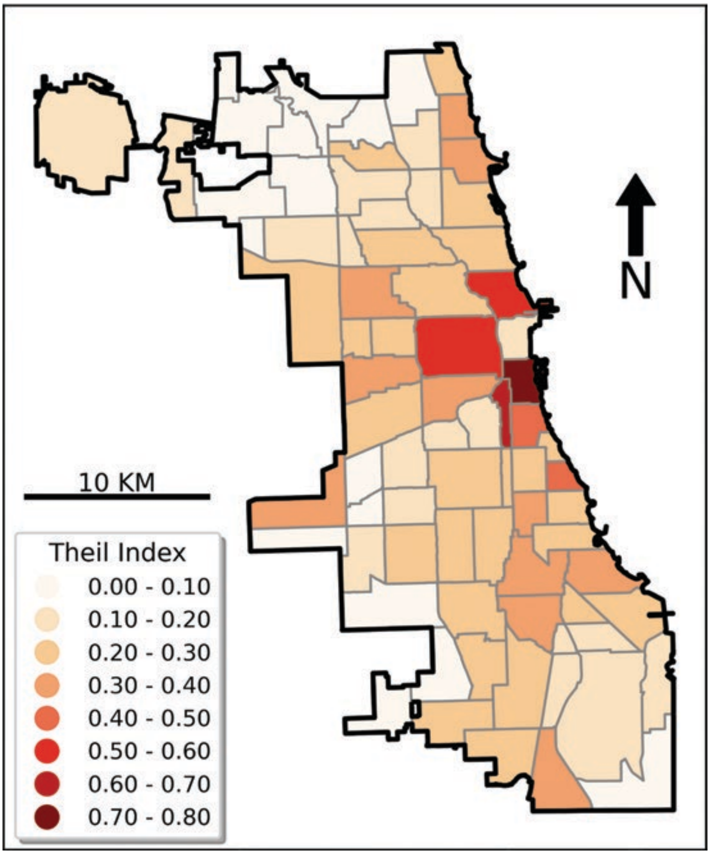

Fig. 5.4 Breakdown of the Theil index within each community area, based on entire 53-year homicide period

Figure 5.5 contains a graph that illustrates those transition probabilities over the entire time period under study. So to read the graph, if the current year (Y-axis) you want to examine is 1966, the transition from the prior year (1965) is on the X-axis. The grid cells are colored according to that transition probability of a homicide occurring in the current year, conditional on a homicide occurring in the previous year.

Along the diagonal of this graph represents all of the 1-year transition probabilities. The lightest colored bin still represents better than random guessing, but is in the range of 0.03 to 0.08 transition probabilities. So, in the early 2000s, where homicides were at the lowest in Chicago, the probability of a repeat homicide micro location dropped to its lowest across. This is true both for 1-year transition probabilities, as it was for longer-term historical probabilities spanning back many years.

Although the diagonal of the graph for the most part illustrates regular consistency for short-term transition probabilities, it clearly shows the strongest consistency in homicides was during the 1960s and early 1970s (the triangle on the lower

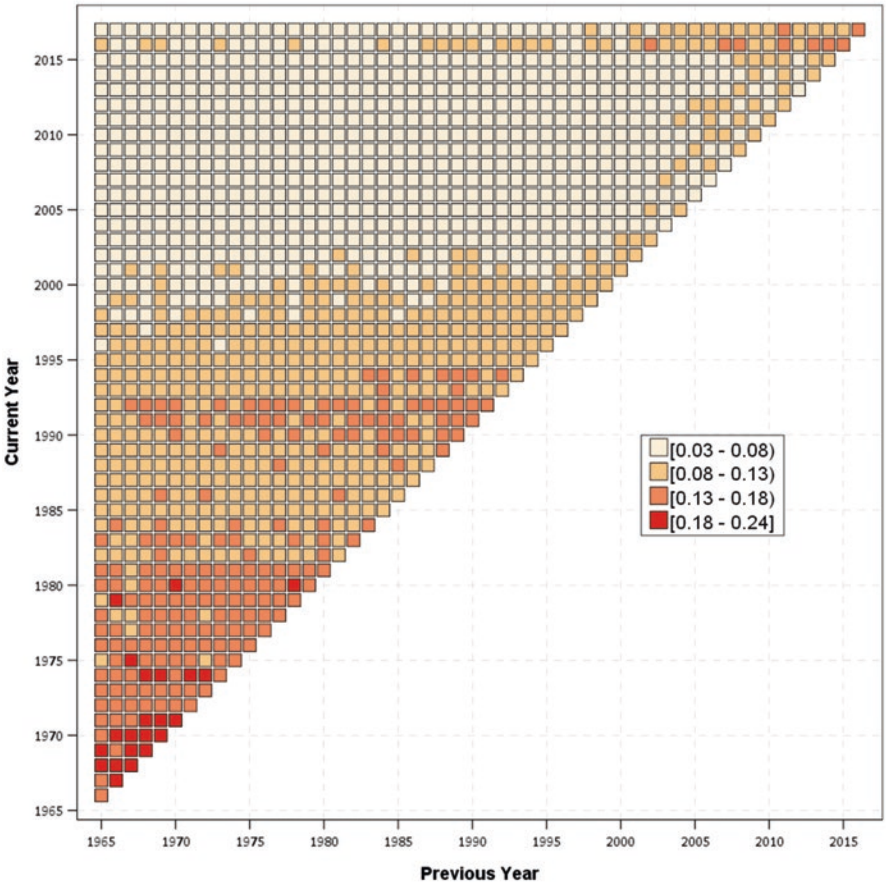

Fig. 5.5 Transition probabilities for t0 (previous year), to t1 (current year). For example, in 1965 there are 335 grid cells with at least 1 homicide. In 2016, 27 of those grid cells also had a homicide, for a transition probability of slightly over 8%

left). The early 1990s increase showed a slightly higher set of transition probabilities (even showing bands going back to the 1960s), but still never crested the highest colored probability bin in the graph relative to the 1960s.

For the recent homicide increase in 2016 and 2017, there again seems to be an increase in the transition probabilities. For 2016, there are slightly higher transition probabilities, mostly limited to the 2000s, but has some evidence of very long-term history going back in spurts to the 1960s. 2017 shows a similar pattern, but the higher transition probabilities are only limited to the 2000s.

Group-Based Trajectory Analysis of Homicides over Time

The prior analysis of the transition probabilities shows some evidence of historical, long-term persistence in micro places that experience homicides. As with the prior clustering analysis, it is mostly a global metric to uncover the overall patterns of such persistence within the city. It however does not tell us anything about a specific location. Is the area on the historical black belt still a contemporary homicide hot spot? Are homicide locations in the west side of Chicago increasing over time? We conduct two additional analyses to help address these *location-specific* questions. The first in this section is estimating group-based trajectory models of homicide locations over time. This provides evidence, for a specific grid cell, as to whether the approximate trajectory of homicides is rising, is falling, or shows some other pattern over the 53-year period. The second, in the following sections, we attempt to uncover specific spatial and temporal hot spots via kernel density maps and SaTScan clusters.

The group-based trajectory models are fit for grid cells with at least one homicide over the 53-year period (n = 10,361), as locations with zero homicides are trivially within a flat trajectory of no homicides over the entire time period. Table 5.3 displays several model fit criteria for mixture solutions from 1 through 11 groups: the Bayesian information criteria (BIC), the log-likelihood of the model, the minimum odds of correct classification among each group, and the minimum of the average posterior probability for each mixture solution with more than one group.

We settle on the nine-group mixture for several reasons. One reason is because it showed a relative asymptote in the BIC compared to the ten-group solution. Another is that ten- and higher-group solutions do not appear to be viable. The 10-group solution identified 1 explosive trajectory (a result of using cubic polynomials), and groups with 11 or more trajectories resulted in warnings of singular variance-

Table 5.3 Absolute model metrics for the different trajectory solutions with varying number of latent classes

Components	BIC	Log-likelihood	Min. OCC[a]	Min. APP[b]
1	−134,687	−134,664		
2	−130,478	−130,431	5	0.90
3	−130,003	−129,934	3	0.75
4	−129,812	−129,719	2	0.63
5	−129,440	−129,325	3	0.59
6	−129,220	−129,081	3	0.58
7	−129,140	−128,978	3	0.54
8	−129,095	−128,910	4	0.54
9	−129,070	−128,862	2	0.57
10	−129,071	−128,840	2	0.54
11	−129,080	−128,826	1	0.51

Table 1: Model selection criteria for group-based trajectory models

[a]Odds of correct classification

[b]Average posterior probability

covariance matrices. Also, several of the trajectories appear to be stable and were identified in earlier mixture solutions. In other words, even if we choose mixtures with more or less components, we would still be discussing very similar paths over time. The minimum odds of correct classification (OCC) shows better results for the lower trajectory groups, as do the minimum average posterior probability for the group solutions. It happens to be that several of the groups show similar trajectories over time and so are somewhat confounded. To address this, we visually present the clusters in time series graphs, to illustrate overall that even though the model identified the unique latent classes, overall they provide very similar interpretations of long-term trajectories over the sample period.

Table 5.4 displays the proportion of the sample assigned to each trajectory group (in terms of the 10,262 grid cells with at least 1 homicide over the time period) as well as the average posterior probability and the OCC for each group. Nagin (2005) suggests that groups should have an average posterior probability of 0.7 or higher and should have an odds of correct classification of 5 or higher. In terms of average posterior probabilities, several of the groups fall below the suggested 0.7 threshold, but are all above 0.57. The odds of correct classification are all much higher than 5, with the exception for group 3 (which happens to be the largest group, and has an average posterior probability of 0.7). So overall although the results are mixed as to how well the model can distinguish between these different trajectory groups, they still provide some quantitative evidence that are useful for exploratory data analysis of the trajectory patterns over time.

Figure 5.6 displays the nine trajectory solutions in several panels of graphs. The lines display the predicted trajectories, and the points display the weighted means for each year and group. The lines, due to the nature of the polynomial function, need to follow a cubic function over the time period. The points illustrate the extent to which the cubic functions are reasonable approximations of the temporal trends over time. For example, if a trajectory followed a step function, dramatically increasing or decreasing in a particular year, a polynomial function would likely be a poor approximation. The points also illustrate the volatility within that particular trajectory group – a larger spread around the trajectory lines show more potential year-to-year fluctuations.

Table 5.4 Relative model fit metrics for each individual latent group in the nine-class solution

Trajectory group	Assigned grid cells	% Sample	Group av. post. prob	Odds corr. class.
1	254	3	0.64	70
2	338	3	0.57	39
3	6148	59	0.70	2
4	1668	16	0.63	9
5	473	5	0.63	36
6	631	6	0.73	41
7	604	6	0.68	34
8	177	2	0.72	145
9	68	1	0.85	841

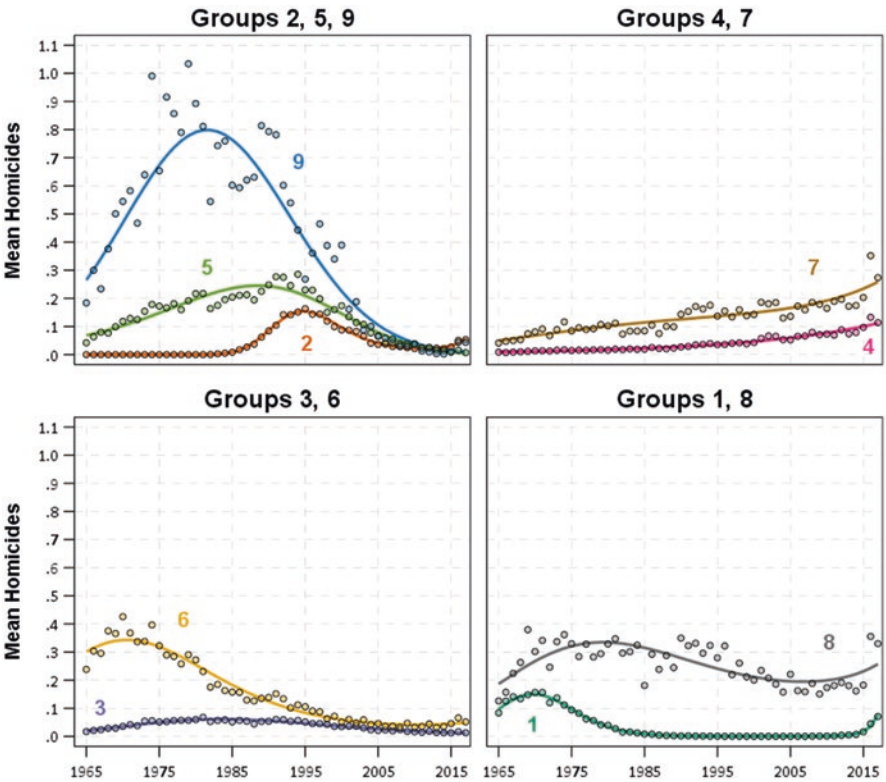

Fig. 5.6 Mean predicted trajectories (lines) and the observed weighted means (circles) for each trajectory group. Groups are separated into different panels to distinguish the lines

The Y-axis on this graph can be interpreted as the average number of homicides expected to occur in a grid cell during a single year, as this is the average of both the zero-inflated portion and the Poisson portion of the latent class models. So at the peak for all trajectories, only a small subset of locations (trajectory group 9) were ever above an expectation of one homicide per year. What this means is that even in very high homicide risk locations, most will not experience a homicide 2 years in a row. This illustrates the need to examine homicides, which are fortunately rare, over an extended period of time. A location could have an average expected number of 0.3 homicides per year, which is very high in this sample, and still only typically have three homicides occur over a 10-year period. Only by examining extremely long periods of time are we able to distinguish such low but historically persistent underlying homicide expectations.

To describe specific homicide trajectories, the top left panel displays three falling trajectories with high levels at the start of the time period; trajectories 2, 5, and 9. The trajectories with lower levels of homicides, but still falling in current data, groups 3 and 6, are plotted in the bottom left panel. The two trajectories with consistently rising trajectories over the time period, groups 4 and 7, are plotted in the top right panel. Finally, the two trajectories 1 and 8 in the lower right panel show somewhat flat, but falling in historical patterns and rising in the most recent years.

Trajectory 9 that peaks in the 1980s and falls afterward was consistently identified in all mixture solutions and as of the six-group solution fell to around 1% of the grid cells. The trajectory labeled 6 that shows a pattern of decreasing since the 1970s, although not as high a peak as 9, emerged in the prior six mixture group and consistently contained around 6% of the sample in subsequent mixture groups. The trajectory labeled 5 shows a rising trajectory over the entire time period and then has a high spike in the weighted mean homicides for 2016. This trajectory emerged as early as in models with three mixtures and dropped to around 6% of the sample in the eight-group mixture. The trajectory group labeled 1 shows a pattern of rising until the 1990s but then subsequently declining. This group emerged in the seven-group mixture and contained around 6% of the sample in both the seven- and eight-group mixtures. The trajectory labeled as 6 was a unique path that first emerged in the eight-group solution. It only contains 1% percent of the sample.

For each trend in Fig. 5.3 you can see that the polynomial predicted trajectory is not a perfect fit compared to the weighted means, but does a reasonable job of describing the overall trend for each trajectory group. An exception to this is group 9, which displays a large amount of variability from 1975 until it begins to decline in the mid-1990s. Another notable exception is that groups 7 and 8 show spikes during 2016. Group 7 and similarly group 4 appear to be slowly rising throughout the time period. These trajectory groups show evidence of homicide dispersing to new areas. Trajectory group 8 shows a high increase in both 2016 and persisting into 2017 (ditto, although less pronounced, for group 1).

This provides visual evidence that groups 7 and 8 (and to a lesser extent groups 4 and 1) are likely candidates for areas in which homicides are displaying a notable increase in the homicide spike in 2016 and 2017 that do not necessarily follow historical trends. But, for group 7 (and 4) these are locations that appeared to be slowly *increasing* over the historical time period. Thus they are not new locations of high risk just exposed in 2016; they are locations that have been slowly increasing in risk over the 53-year period.

Figure 5.7 displays the cumulative proportion of homicides attributable to each trajectory group for each year over the period. These graphs are based on the observed counts (not the estimated expected number of homicides), assigning a grid cell to the trajectory group with the highest posterior probability. So although trajectory group 9 had the highest expected number of homicides starting in 1965, groups 3 and 6 contributed a much larger proportion of the total homicides in the city. This is due to a much smaller number of grid cells in group 9 (68), versus group 6 (631) and group 3 (6148).

For example, in 1965 there were a total of 396 homicides. Of the 68 group 9 grid cells, they experienced 10 homicides overall. Those 10 homicides then are $10/396 \approx 3\%$ of the total number of homicides in 1965. Figure 5.4 then shows transitions of how particular groups influence the overall homicide trends in the city – a group that contributes a larger proportion will have more sway on the overall city-level homicide counts. So while group 9 showed the highest expected homicide rate,

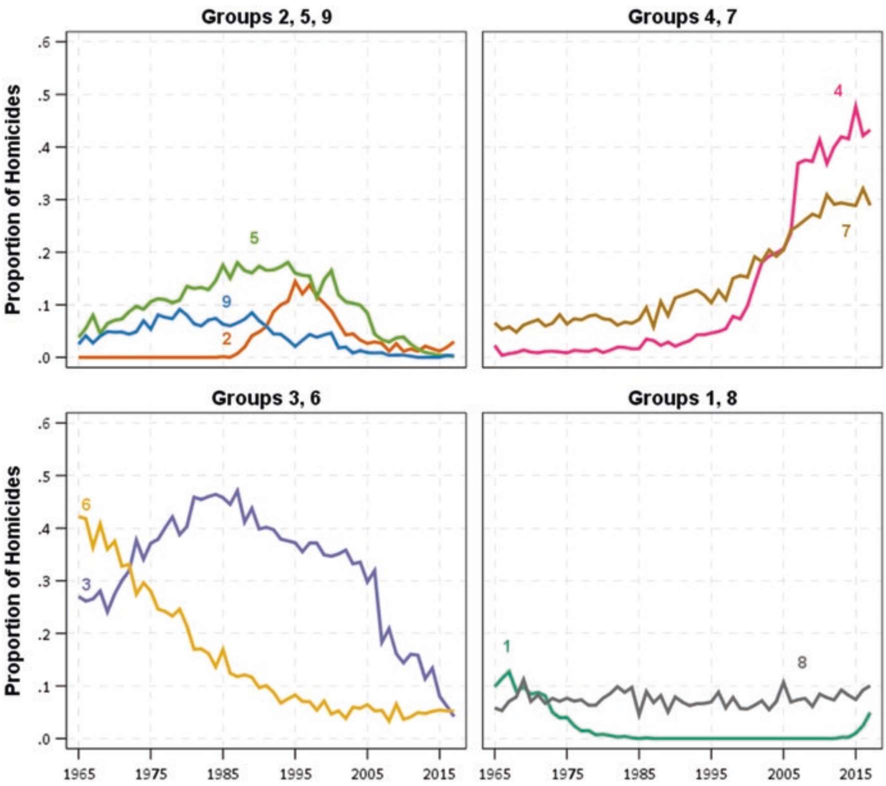

Fig. 5.7 Proportion of homicides in Chicago attributable to each trajectory group

overall it only contributes a small portion to the overall city-level homicide trends over time. The panels in the lower left (declining groups 3 and 6) and the upper right (groups 4 and 7) thus appear to be better indicator of overall city-level homicide patterns.

Group 6 started as the group accounting for the largest proportions of homicides in the entire time period, but rapidly declined to account for very little in the total proportion of homicides through the sample time period, bottoming out at around 5% of the total citywide homicide contributions in the late 1990s. And group 3 initially rose from the mid-1960s into the early 1990s, almost peaking at accounting for nearly 50% of the city's total homicides, and then experienced a dramatic drop starting in the late 1980s and more steeply declined in the mid-aughts.

Figure 5.7 shows then a transition into the micro grid cells that contribute the largest portions of homicides, from groups 3 and 6 to groups 4 and 7. Groups 4 and 7 start to however gain a much larger proportion of the citywide homicide counts not in the most recent high spike of 2016 and 2017, but started their upward trend in the mid-1990s. The 2016 spike is visible in the graph, but appears to simply be part of a longer-term trend of increasing homicides proportionally occurring in these particular areas.

Group 8 in Fig. 5.7 shows a relatively consistent proportion contribution to the overall citywide homicide totals, around 10%, over the entire time period. So although its expected homicide oscillates slightly in Fig. 5.6 over the entire 53-year time period, these are locations that appear to be the most historically consistent high homicide locations over the entire sample. While other groups wax and wane, 20–30% of these 177 grid cells appear to experience a homicide on a yearly basis. This does not matter if one is talking about 1965 or 2017.

Figure 5.8 displays a small multiple map of each trajectory group, showing the spatial locations for these groups. Clear spatial patterns emerge for the trajectory groups with a smaller number of grid cells. Groups 6 and 9, which showed declines in expected homicides over time, are clustered in the eastern part of the city (mostly following South State Street) and running west (mostly following West Madison St moving into the Garfield Park neighborhood). Group 6 also has a cluster on the Gold Coast, in the northern part of the city.

Group 7, the high rising trajectory that showed the most pronounced spike in 2016, is dispersed in areas in South and West Chicago that have historically shown high homicide rates. The other trajectory groups show a wide amount of dispersion across Chicago, both for the rising group 4, the falling group 3, and group 2 which showed a hump centered on 1995. As with prior work examining crime trajectories over long periods of time, one can find plenty of instances where different trajectories are nearby one another in space, suggesting larger neighborhood areas are not monolithic in their spatial and temporal patterns of crime.

We have additionally provided an interactive map of the trajectory groups. The map also includes locations of former high-rise public housing and gang territories in Chicago. This map can be accessed on the internet at https://apwheele.github.io/MathPosts/TrajectoryMap.html. Figure 5.9 displays a screenshot of superimposing trajectory group 9 and the public housing projects. Note these include current projects as well as projects that have been demolished. (Clicking on a project polygon displays a pop-up giving the name of the project, the total number of units, and its current status of demolished, rehabbed, or sold.) Trajectory group 9 clearly has a large spatial overlap with several different public housing projects. The observed trajectory path of this group is not inconsistent with it falling due to moving tenants out of the high-rise public housing projects and demolition, as this trajectory appeared to fall beginning in the early 1990s, and had a large dip in the weighted means from 2000 to 2001. The year 2000 is when group 7 eclipsed group 9 as the trajectory with the highest expected number of homicides in the city.

Examining whether gang territories are significant contributors to different trajectories is much more difficult. Supposed gang territories cover much of Chicago, and subsequently one can find overlap of gang territories with any particular homicide trajectory group. More specific indicators of gang intensity and rivalry would likely be needed to assess whether particular grid cells are associated with particular gang territories (Fig. 5.10).

Finally, we also include an estimate of the clustering, but using the underlying latent trajectory estimates, instead of the observed counts. Figure 5.11 displays the Gini clustering metric, but using the latent class estimates instead. The overall cor-

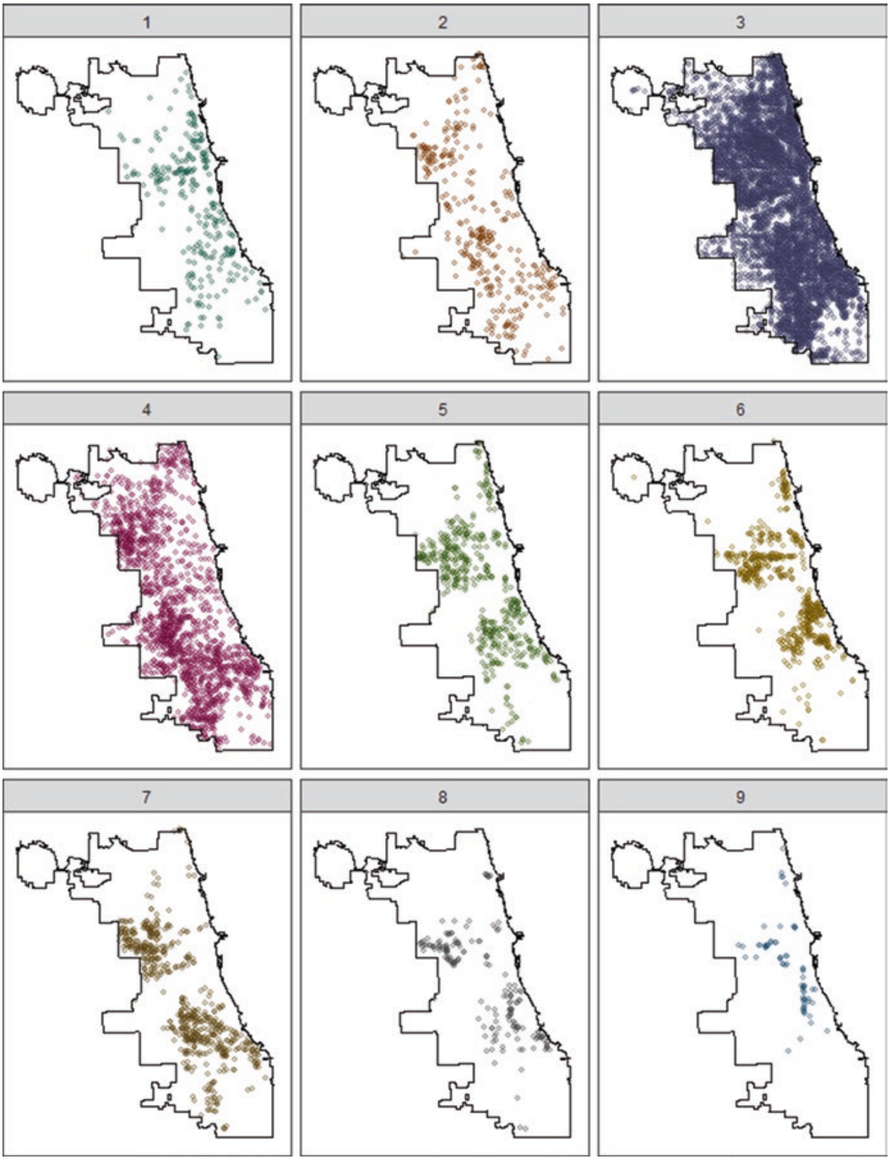

Fig. 5.8 Pin map of the locations of the trajectory groups

relation between the two measures is 0.57, but they do not appear to be strongly related to one another, besides the fact that the generalized Gini is a consistently smaller value. In terms of overall trends, the latent Gini estimate shows the highest clustering in the earliest time period in the mid-1960s. The trend then decreased into the early 2000s and started rising into the latest time period. The latent Gini estimate shows a much smoother transition, partially due to the fact it is a superposition of

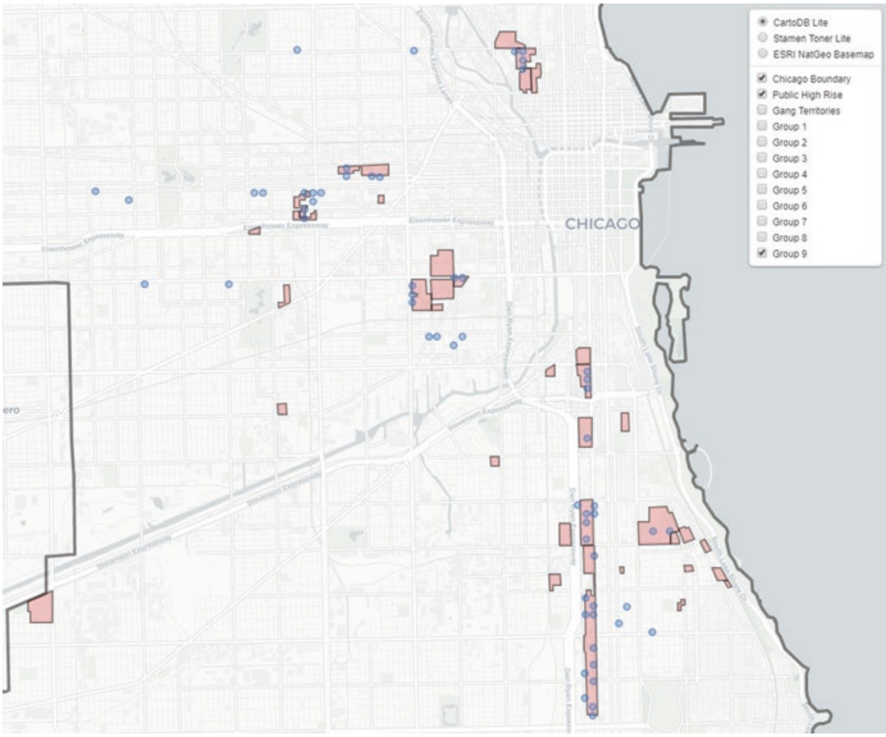

Fig. 5.9 Screenshot of interactive Leaflet map, using a CartoDB basemap, overlaying trajectory groups, high-rise public housing, community areas, and gang territories. Map is available at https://apwheele.github.io/MathPosts/TrajectoryMap.html. This map displays trajectory group 9, which shows high overlap with several different locations of former high-rise public housing projects

several mixtures of polynomial functions; thus it is easier to identify longer-term trends, and the generalized Gini based on the observed homicide counts is a much noisier estimate from year to year. From the latent Gini estimate, one might conclude that overall clustering is not directly tied to more or less homicides overall.

Hot Spot Clusters via Kernel Density and Highest Density Regions

The prior longitudinal clustering analysis provided mixed results as to the ultimate question of whether homicide patterns were spreading out in the recent uptick in 2016 and 2017, versus occurring at a higher intensity but in the same historical locations of high homicide risk. The prior trajectory groups do not include any spatial components, so end up displaying confusing spatial patterns, where a rising and falling trajectory group appears to be superimposed in the map in the same general

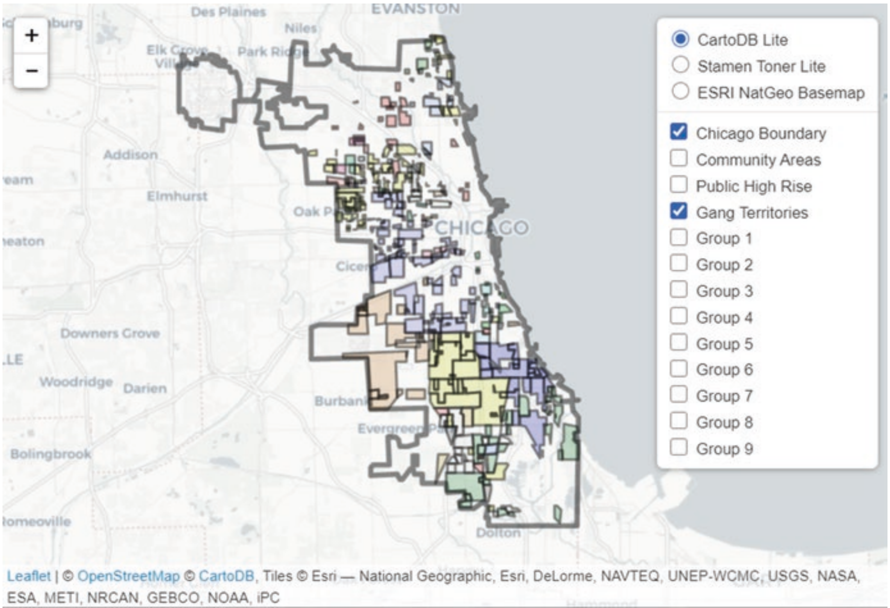

Fig. 5.10 Screenshot of Chicago gang territories Leaflet map. Since gang territories cover much of the city, it is difficult to discern any particular patterns with individual homicide trajectory groups or other clusters of homicides. Map is available at https://apwheele.github.io/MathPosts/TrajectoryMap.html

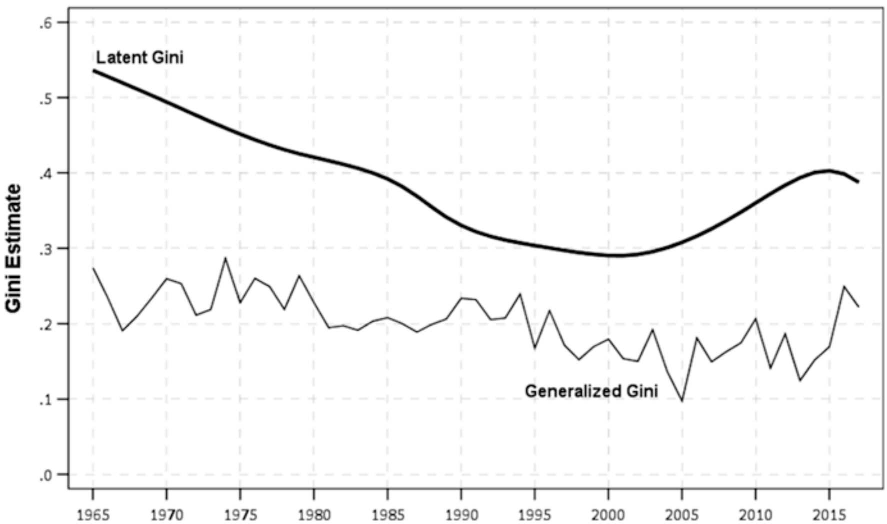

Fig. 5.11 Gini estimates based on the generalized Gini versus the estimate using the latent class trajectories

areas. To attempt to uncover specific hot spots, while taking into account space, we attempt to identify clusters using kernel density maps and space-time clusters directly. This comes at the cost of enforcing geographic homogeneity, even though some of the underlying locations may indeed be following diverse trends.

Figure 5.12 displays a kernel density estimate for each 5-year period as a continuous color ramp, as well as the 50% highest density region as a contour line (Hyndman 1996). So the contour lines show the area within each map that capture approximately 50% of the total homicides. As such, smaller areas show more concentrated homicides, whereas larger areas signify homicides are spreading out to a larger degree (although are not necessarily increasing, as there will always be a 50% relative line even if the total number of homicides is small).

The kernel density estimate uses a bivariate normal kernel, with a bandwidth of 750 m. Points submitted to the calculation were assigned to the centroid of the 150 by 150 m bins. Using a larger bandwidth would further spread out the density and create larger areas, so a smaller bandwidth of 750 m provides a more detailed map. 750 m was specifically chosen as it was used to reasonable effect in Block (2000) with a similar grid of 150 by 150 m grid cells in Chicago.

Figure 5.12 shows very similar geographic concentration over time. While the map displays a smaller and more concentrated area in the 1965–1969 map, they are still centered on the neighborhoods in the west side and the south side areas of Chicago. The 50% region expands in later periods, but are still centered on those same two neighborhoods over the 50 years. Larger 50% highest density regions in any map signify that there is *less* clustering – they do not correspond to increases or decreases in the total number of homicides. Each map in the panel would identify the highest part of the density distribution, and this would occur even if there were very few homicides during that time period. This can be similarly seen by the fact that the color ramp for the kernel density appears lighter in different time periods compared to the 1965–1969 period which shows more saturation in particular areas of Chicago. These maps tend to confirm similar spatial patterns as identified by scholars examining spatial trends in Chicago using census tracts or larger neighborhood areas.

To better illustrate this historical consistency, Fig. 5.13 only displays homicides in 2013 through 2015 (n = 1347 homicides) vs 2016 through 2017 (n = 1448 homicides). So although the map on the left encompasses 1 more year, they have approximately the same number of homicides occurring within each map, thus making the density estimates approximately comparable. From this map, it appears the patterns are very consistent over time, suggesting that homicides *are not* spreading out into new areas, but are simply reoccurring in historically areas of high homicide density, at least compared to the most recent prior years.

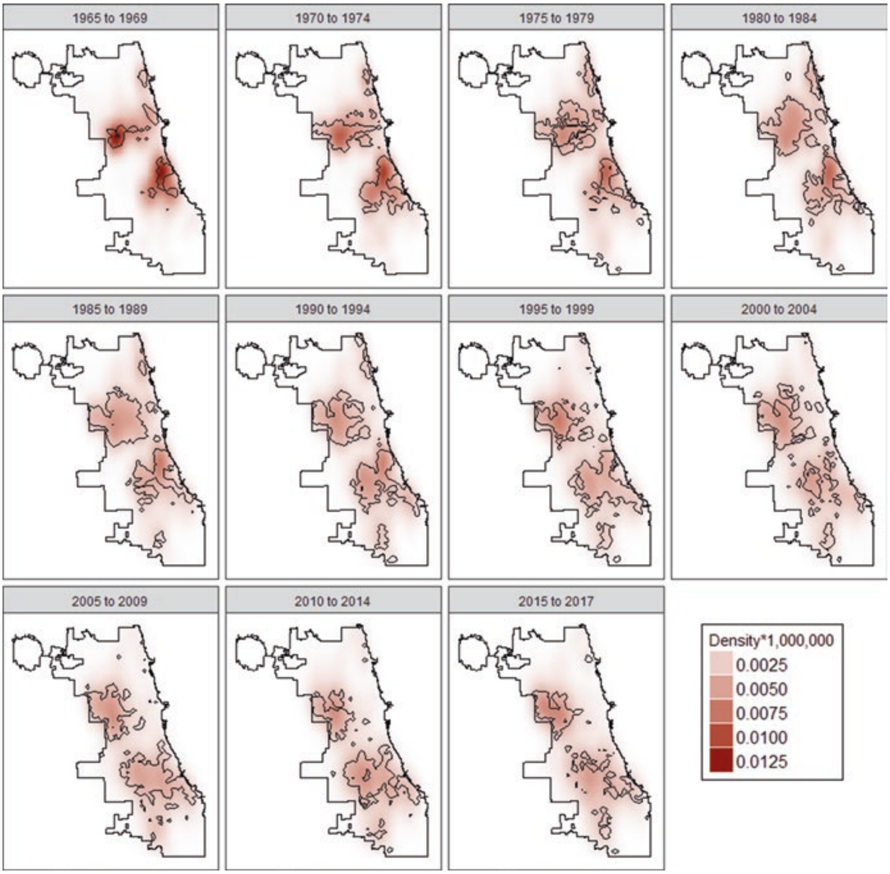

Fig. 5.12 Kernel density estimate and 50% highest density regions (displayed as a black contour line) per each 5-year period. Based off of kernel density estimate of homicide data binned to the centroid of 150 m × 150 m grid cells. Kernel is bivariate normal with a bandwidth of 750 m

Space-Time Clusters via SatScan

The prior kernel density estimates only take into account time via conducting the analysis on different temporal slices of the data. To attempt to uncover specific clusters of homicides both in space and in time, we use a procedure to identify statistically significant space-time clusters. Table 5.5 displays the SaTScan results for nine statistically significant space-time clusters (based on a Monte Carlo random simulations) for clusters that include more than one area. (Some grid cells with multiple homicides include a singlet cluster, which are eliminated from this analysis.) There end up being multiple clusters of various sizes spanning almost the entire time period under analysis. Figure 5.14 shows the spatial locations of each of the clusters, with the IDs corresponding to the cluster IDs displayed in Table 5.5.

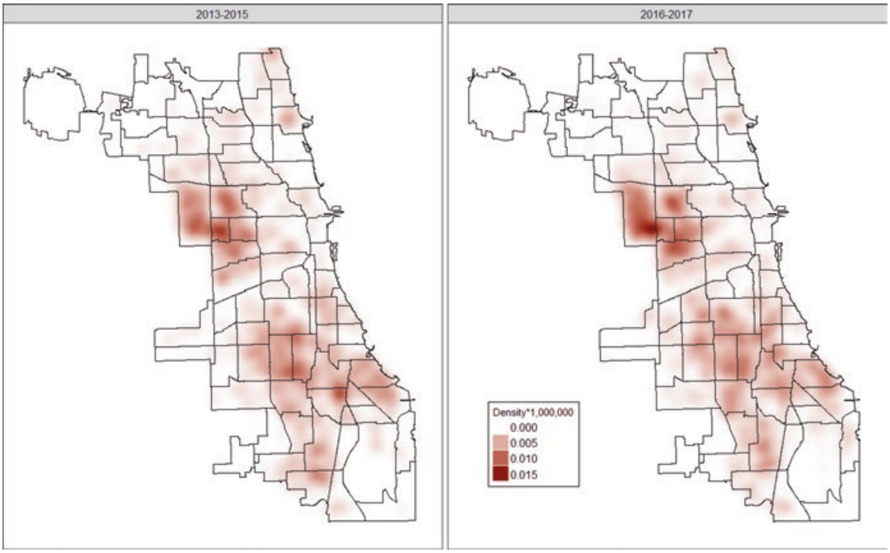

Fig. 5.13 Comparison of kernel density estimates of 2013–2015 versus 2016–2017 homicides. The left panel contains 1347 total homicides over the 3-year period, and the right panel contains 1448 homicides over the 2-year period. So the density estimates have a similar saturation between the two panels

Table 5.5 SaTScan cluster statistics for nine clusters

Cluster ID	Radius (meters)	Begin	End	# Grid cells	Observed hom.	Expected hom.	Relative risk
1	4170	1968	1972	837	907	275.8	3.4
2	3689	1970	1974	1367	1080	450.2	2.4
3	3330	1990	1994	1129	675	371.8	1.8
5	2250	1977	1981	181	193	59.6	3.3
6	1544	1975	1979	141	144	46.4	3.1
7	1477	1990	1994	192	160	63.2	2.5
8	4986	2016	2017	1014	231	133.7	1.7
9	212	1990	1992	8	18	1.6	11.4
11	960	1994	1997	104	71	27.4	2.6

In terms of the recent uptick in homicides in 2016 and 2017, there ends up being only one cluster, number 8, that includes a wide area in the west area of Chicago, centered on the Austin community area. It ends up being in this area, with a radius of nearly 5 km (although much of that radius includes area outside of the city that does not contribute to the overall cluster statistics), and had 231 homicides over that 2-year period, when only 134 were expected, for a risk ratio of 1.7. Homicide before the uptick in 2016 and 2017 averaged around 450 per year, whereas in 2016 and 2017, they averaged around 700. Thus this one particular space-time cluster only accounts for around 20% (~100/500) of the total homicide increase.

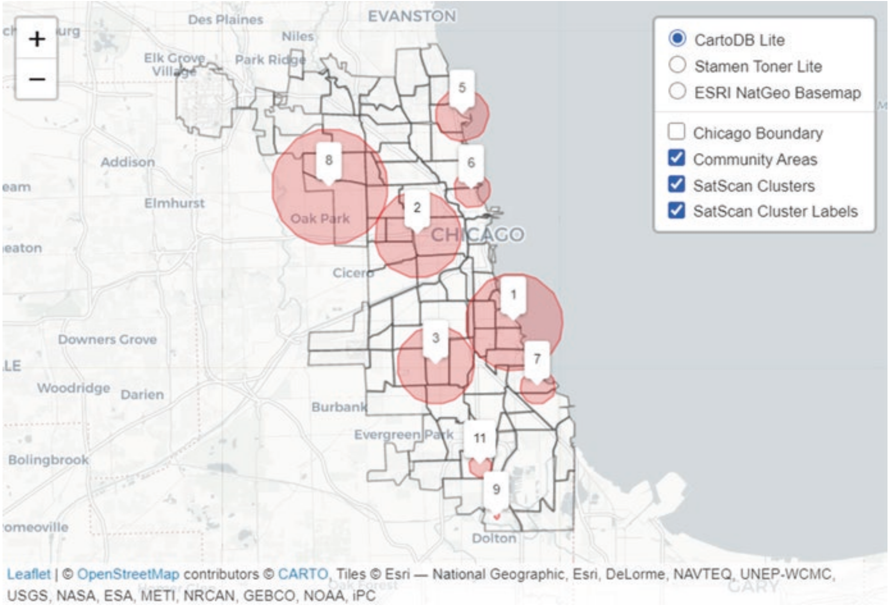

Fig. 5.14 Screenshot of interactive Leaflet map showcasing the nine SaTScan clusters superimposed over Chicago community areas. Map is available at https://apwheele.github.io/MathPosts/SatScanMap_Leaflet.html

Clusters are identified throughout the temporal period under study, but a few notable absences occur – there are no clusters in the flat period (of relatively higher homicides) in the 1980s, and no clusters identified in the lower homicide period of the 2000s (and only one 2016–2017 cluster).

The algorithm itself can potentially return clusters of up to half of the study length and can also return clusters of one single year as well (although we eliminate several 1-year, one-grid cell clusters from this analysis). The longest time period however identified ends up spanning 5 years. There are three clusters in the 1990–1994 time period (the period with the highest homicide totals, with the exception of 1974). The early 1990s clusters correspond to the southern part of Chicago, with one being centered on the South Shore community area (cluster ID number 7), another centered on Riverdale (cluster ID number 9), and the last centered on the West Englewood community area (cluster ID number 3). Another 1990s cluster, ID 11, was also in the southern part of the city, centered on Roseland from 1994 to 1997.

While cluster 1, from 1968 through 1972, is toward the southern part of the city (centered on Kenwood on the eastern coast), the remaining historical clusters appear to be more toward the northern and western areas of the city and are further in the past. Cluster 5, centered on the Uptown community area, spans from 1977 through 1981. Cluster 6, spanning 1975 through 1979, is centered near the border of Lincoln Park and the Near North Side.

Overall, such maps agree with the prior trajectory analysis, suggesting homicide persistence is not per se the norm in Chicago. Various ups appear in different areas of the city, and there is no consistent area of high homicide increases discovered. This does however point to the cluster 8, centered on the Austin neighborhood, as the most likely location to show diffusing homicides to new areas in the recent uptick in 2016 and 2017. This is also visible in Fig. 5.13, showing a slightly higher density in this westernmost community area compared to the prior several years.

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Chapter 6
Conclusion

Abstract This volume set out to answer three specific research questions detailing the continuing problem of homicide in the city of Chicago. Over the entire 53-year study period, homicides approximately conform to the laws of crime concentration – just 5% of the micro places contain about half of the 36,176 homicides in the study. We address several of the limitations of the multi-method approach that was used. The importance of this work is improving public policy and advancing criminological theory. We clearly illustrate the need for researchers and public policy analysts to go beyond near-term crime patterns and examine crime patterns in a historical lens to uncover both contemporary and historical causes for spatial and temporal hot spots of crime.

Keywords Homicide clustering · Crime clustering · Global clustering analysis · Historical homicide locations · kernel density estimates · SaTScan clustering · Group-based trajectory models · Community criminology · Non-domestic interpersonal disputes · Micro places

Given the complexity of the prior findings, it behooves us to recap the findings in as simple as language as possible, combining the interpretation from the multiple analyses.

First, in reference to Research Question 1, *do homicides cluster*, we ultimately find incontrovertible evidence that this is the case through various analyses. Over the entire 53-year period, homicides approximately conform to Weisburd's law of crime concentration – 5% of the grid cells contain just under 45% of the homicides in the sample.

Breaking this research question into a temporal component – is the amount of clustering temporally invariant, or do the recent spikes in crime clustering result in more spread out or more clustered homicides, is frustratingly difficult to discern given the various exploratory data analyses presented in this research.

Several of the different global clustering analyses, using either the generalized Gini coefficient, or the Gini coefficient estimated based on the underlying latent

A. P. Wheeler et al., *Micro-Place Homicide Patterns in Chicago*, SpringerBriefs in Criminology, https://doi.org/10.1007/978-3-030-61446-1_6

trajectories, gives some evidence that homicides were the most clustered in the early stages of the sample, during the 1960s. Clustering then fell throughout the sample period and then rose back up with the recent homicide spikes in 2016 and 2017.

This segues into our second research question, *do micro places show long term historical persistence in high homicide risk locations*? For a simple analysis, we show transition probabilities over the entire time period. When guessing whether a 150-by-150 meter grid cell in Chicago is likely to have a homicide any particular year is never much over 3%, if you know that a grid cell had a homicide in the prior year, that percent increases to 13%. Even over very long periods of time, if a grid cell had a homicide in 1965, the probability that grid cell also experienced a homicide in 2016 was over 8%. Thus, there is clearly some historical persistence in homicides at micro places.

The group-based trajectory analysis provides graphical evidence for different homicide trends over the entire time period. These are perhaps the most intriguing results we provide, which show evidence of varying trajectories in the 1960s, and transitioning to higher crime locations in more recent data.

The highest crime trajectory group 9 shows clear evidence supporting prior work that the demolition of large public housing complexes decreased crime (Smith 2014). The other crime generator we examine, gang territories, does not show any clear relationship however to any of the homicide trajectories. This is because the public gang territory file we use shows very little discrimination; much of the city of Chicago is covered by some purported gang territory. A more valid measure of not only gang territories but gang intensity or rivalry is likely needed to better identify if gangs are spatially associated with these homicides.

Unfortunately, we are not able to directly tie homicides to whether they involve a gang member (such as the victim is a known gang affiliate). While we are able to show the volatility in homicides is entirely attributable to non-domestic homicides (domestic homicides have a near perfectly flat downward trend over the entire time period), we are not able to further break these down into gang related based on the limited information available in the public Chicago homicide dataset.

Additionally, our trajectory results show the first evidence of long-term changes in the underlying trend of crimes at micro places. Prior trajectory analyses for different crimes, over shorter time periods (such as a decade or two), tended to show very long-term historical consistency (Weisburd et al. 2004; Curman et al. 2015; Wheeler et al. 2016). Those patterns are visually simple to decode in time series graphs, but when plotting in maps presents more questions. While group 9 shows clear associations with public housing, we were unable to detect any obvious other patterns. While several of the trajectories show clustering, the cluster locations are superimposed in a way that makes interpreting simple patterns, such as saying community A increased in recent years whereas community B decreased, more difficult to determine.

This provides the backdrop to our last research question, what is the main reason to motivate the entire analysis; are the 2016 and 2017 homicide spikes attributable to historically high homicide risk locations, or are they the result of previous unforeseeable patterns based on historical spatial homicide patterns in Chicago?

Again, somewhat frustratingly, given the variety of analyses we have performed, one could cherry pick pieces of our results to justify a myriad of conclusions. For example, the clustering results suggest the most recent homicide spike increased crime clustering, suggesting homicides are more intense at historically high homicide areas.

For example, one SaTScan cluster identified a homicide cluster in the western portion of the city in 2016 and 2017. Since this area is historically a high homicide location in Chicago, one may conclude that it was always an area of high homicide risk.

This interpretation is also supported by the analyses of the kernel density estimates and highest density regions. For the kernel density map displaying 5-year intervals, the highest density region in the 1965–1970 time period shows much more intensity in a small area. Later time periods then appear to be more diffuse throughout Chicago, although still show historical consistency for general hot spots in the western and southern parts of Chicago. Subsequently the kernel density map for the more recent temporal periods of 2013–2015 versus 2016–2017 shows evidence of a more intense hot spot in the Austin community area in the western most part of Chicago.

However, the SaTScan cluster in 2016–2017 can only reasonably explain around 20% of the recent homicide increase, an extra 100 homicides in that particular area, whereas the city experienced approximately an extra 500 homicides in 2016 and 2017 compared to recent historical patterns in the prior 10 years.

When interpreting the group-based trajectory model, results also paints a more complicated picture. It appears that several of the trajectories swapped the areas that contribute the most homicide risk to the city, and these patterns appeared to occur **before** the homicide increases in 2016 and 2017.

Before proceeding to addressing why these results are important for policy and for theoretical crime patterns, we address several limitations of the analyses we present here. First, while we take pains to attempt to deal with issues of the modifiable areal and temporal unit problem through various analyses, it appears taking shorter temporal samples results in substantively smaller estimates of the generalized Gini coefficient for clustering and that smaller community areas result in higher estimates of clustering according to the Theil metric. A similar problem has been previously identified in studies examining repeat victimization (Park and Eck 2013). We do not offer any special advice here about what is the right temporal span or geographic area with which to examine homicides or any type of crime; we simply hope any conclusions based on the observed patterns are reasonably robust to whatever temporal unit we choose.

To this end, we hope providing the results using a variety of methods and temporal breakdowns helps pre-empt any particular false inferences that would be attributable to conducting the analysis on any particular geographic or temporal resolution. We however cannot be certain that such units of analysis do not bias our findings in a particular way. It may either be that examining micro units places too much emphasis on the trees and their potential volatile patterns, as opposed to identifying more widespread patterns that examining the entire forest of community areas would uncover. Similarly, if one examines large community areas from the start, it may mask important micro level patterns. We hope that our analysis is useful for the analysis of micro places – that communities are not monolithic in their risk, and treating them as such is likely a mistake. But we cannot be certain, nor would we argue that making arbitrary micro place grid cells are ultimately the best spatial unit of analysis.

Another limitation of the current study is the use of group-based trajectory models to cluster grid cells into unique temporal paths. One needs to be wary in assigning too much significance to the underlying trajectories, as one will often find trajectories even in random data (Skardhamar 2010). Taylor (2015) in his recent book, *Community Criminology*, makes the point that hot spots are artificially constructed – they are often not spatial units one can physically observe (like a street segment or a particular building). Empirically identifying a hot spot of high crime does not make it physically exist anywhere besides in the algorithm that created it. A synonymous quote popular among geographers is “a map *is not* the territory” (Korzybski 1931). Making a circle on a map and labeling it a hot spot does not make it a real entity. There is a direct analogy to constructing unique temporal trajectories. We do not make the claim here that these trajectories definitively exist, we simply use them as a convenient descriptive tool to describe complicated temporal data. This is similar to how a hot spot map can make sense of noisy crime data, and we use group-based trajectory models to similar ends.

Given that group-based trajectory models (as we have estimated them here) do not contain a geographic component – they are spatially ignorant – it may be reasonable for future data analysis to attempt to bridge such a limitation. One may attempt to spatially smooth trajectories by fitting the multinomial part predicting the latent class via spatial terms, such as tensor splines. Or one may attempt to incorporate spatial autocorrelation into the temporal trajectories, so the estimate temporal trajectories reduce both temporal and spatial autocorrelation.

Given our lack of spatial measures covering the entire time period, we also cannot pin particular trajectories to characteristics of the built environment. While we have uncovered one that is likely tied to a particular trajectory group (large public housing), no doubt there are others that we were unable to uncover. This similarly could be useful to incorporate into a model predicting long-term trajectories. For spatially invariant characteristics, such as long-term zoning, it may be the case particular trajectories are more associated with particular commercial zoning types. For temporally variable geographic characteristics, they may influence the overall temporal patterns as well.

The final limitation we list here is that the study is largely exploratory. We cannot identify any particular impetus that would explain the dramatic increase of homicides in 2016. While previous homicide trends in the 1970s and 1980s in Chicago had increases of over 100 homicides in several years, the increase from 498 homicides in 2015 to 781 homicides in 2016 is unique in its magnitude. Examining domestic vs other homicides in the sample, it appears the majority of fluctuations (both current and historical) are not due to domestic homicides, which have dropped from slightly over 100 in 1965 to around 50 currently in a near linear trend over that time period (Block and Christakos 1995).

Given these limitations, we now turn to the importance of our work for policy and our understanding of criminological theory. Understanding the underlying *causes* of the recent increase in homicides is necessary to make strong statements about either.

So it seems likely such volatile patterns are due to rises and declines in non-domestic interpersonal disputes (Block 1987; Griffiths and Chavez 2004). While we suspect public violence is a driver of the increase, and that gang violence is a potential explanation, we were not able to discern any obvious spatial relation between gang territories and high homicide micro places. This is partly because gang territories cover much of the city. More appropriate geographic measures that do not entirely rely on the geographic extent of gang territories, but also include measures of gang intensity (Block 2000), might provide a clearer picture of how gang behavior influences the spatial distribution of homicide. This is in addition to specifically examining homicides that are affiliated with gang members or are known to have a gang-related motivation.

The homicide increase comes at a time in which police in Chicago have reduced their proactivity, the so-called Ferguson effect (Cassell and Fowles 2018; Towers and White 2017). This analysis cannot verify nor deny such an effect. For example, although other work has suggested that micro place-based policing practices may have contributed to crime declines in New York City (Weisburd et al. 2014; Wooditch and Weisburd 2016), New York City has also seen subsequent dramatic declines in stop, question, and frisk activity due to civil litigation (Sweeten 2016), but no subsequent increase in major crimes. Simultaneously other factors in Chicago could alternatively contribute to the homicide spike – such as lack of confidence and cooperation with the police, or a recent poor record of clearing homicide cases. Future researchers should examine these covariates in relation to homicides over time to be able to make any inferences about their effects. It could also be that the homicide increase is simply the result of typical volatility in homicide patterns (Wheeler and Kovandzic 2017). If one monitors a particular crime trend over a long enough period of time, one will uncover some seemingly anomalous up (or down) blips. Such volatility appears to be normal when examining city-level homicide rates (Wheeler and Kovandzic 2017), as so are ultimately not dispositive that an increase signifies an actual change from the underlying historical homicide rates.

It is easy to provide a Monday morning quarterback analysis, but given the complexity of the patterns we uncover here, it is unlikely anyone could have reasonably conducted any spatial or temporal forecast that would have accurately captured the complicated patterns we uncover here. So despite all of our analysis, we are still a far ways away from saying such models could reasonably capture complicated, long-term, spatial, and temporal homicide dynamics in Chicago.

This recent spike however provides a unique test for examining the temporal stability of crime at micro places from a theoretical perspective. All previous examinations the authors are aware of were for cities in which crime was consistently declining over the observed time period. Our findings show that such homicides were still mainly concentrated among locations that historically had high levels of crime, and the trajectory that contributed the most to the recent increase had been previously rising over entire sample time period. This provides further evidence for the tight coupling of crime and place, even during a time of great change in temporal crime patterns and even when examining the rarer crime of homicide. In turn that suggests that any law enforcement intervention to prevent homicides should likely have a geographic focus.

Given our findings are unique in terms of identifying long-term changes in micro places that contribute to the majority of homicides, it gives us pause on saying prior analyses illustrate long-term historical persistence in crime patterns. Were the prior results an artifact of too small of temporal analysis? Given the rarity of homicide, it seems unlikely we would have uncovered any interesting long-term patterns if one took a smaller slice, such as one (or even two) decades. To uncover such long-term temporal trajectories in the underlying homicide risk, it was likely necessary to observe the homicides over multiple decades.

Because of this long-term dataset and analysis, we were able to paint a much more complicated picture, beyond that of the historical Chicago school of crime that shows ecological consistency in crime patterns. While a limitation of our work is that we again cannot say what micro place characteristics ultimately explain these transitions, it illustrates the need for criminologists to go beyond near-term crime patterns and examine crime patterns in a historical lens to uncover both contemporary and historical causes for spatial and temporal hot spots of crime.

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Index

A. P. Wheeler et al., *Micro-Place Homicide Patterns in Chicago*, SpringerBriefs in Criminology, https://doi.org/10.1007/978-3-030-61446-1