The Importance of Small Units of Aggregation:
Trajectories of crime at addresses in Cincinnati, Ohio, 1998–2012

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ABSTRACT AND ARTICLE INFORMATION

We describe the temporal and spatial patterns of crime at unique addresses over a 15-year period, 1998-2012, in a medium-sized Midwestern city. Group-based trajectory analysis of police incidents recorded by the Cincinnati Police Department are combined with geographic analysis for the entire city, while also highlighting individual address points in one high-crime neighborhood. We find that six trajectories adequately describe the city-wide data, with the low-stable crime trajectory comprising the majority of the places, while the high-stable crime trajectory is just 2.5% of addresses yet consistently has one-third of crime, which accounts for a disproportionate amount of crime. Similar to previous research at the street-block level, small differences in city-wide trends from 1998-2012 obscure large differences within trajectories. Places with very different trajectories of crime are very often located on the same street segment. Nearly all high-crime addresses exist among a cloud of low-crime places. This suggests that characteristics of individual addresses are of importance both to crime theory and crime prevention practice.

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The traditional focus of criminologists is on people. Environmental criminology focuses on crime events. Broadly speaking, this is the difference between the propensity of an individual to commit crime and the opportunities available to that individual—the difference between criminality and opportunity (Hirschi, 1986). Environmental criminology has found that the opportunity for crime is impacted by the built environment (Crowe, 1991; Jeffery, 1971; Newman, 1972), routine activities of both offenders and victims (Cohen & Felson, 1979), and the actions of place managers (Eck, 1994; Felson, 1995). This has led some researchers to examine the characteristics of places that are conducive to crime.

Place-based studies have a long history in criminology (for a detailed history, see Weisburd, Bruinsma, & Bernasco, 2009). In the modern era, the field began to focus on places relatively recently with Sherman, Gartin, and Buerger (1989). The idea that some places have more crime than others—of crime “hot spots”—is now common knowledge among both academics and practitioners. Further, we know that crime can cluster in both space and time (Weisburd, Bushway, Lum, & Yang, 2004). This paper adds to this literature by examining crime at the smallest unit...
of aggregation currently available, the street address, across both time and space. We use group-based trajectory analysis combined with spatial analysis to examine trends of crime in Cincinnati from 1998–2012.

Place-Based Crime, Group-Based Trajectory Modeling, and Place-Based, Group-Based Trajectory Modeling in the Literature

Place-Based Crime

Crime is introduced into a time and place by opportunity (Brantingham & Brantingham, 1981; Felson & Clarke, 1998). If we remove, or alter, the opportunity for crime, we are able to reduce the amount of crime that occurs (Cohen & Felson, 1979). While traditional criminology focuses on the elements that might motivate an offender to commit crime, environmental criminology focuses on the overall totality of circumstances, particularly elements beyond the offender, that provide the opportunity for crime (Brantingham & Brantingham, 1981; Wortley & Mazerolle, 2011). Within environmental criminology, the study of routine activities tells us that crime will only occur when a victim and a motivated offender are given the opportunity to converge in time and space (Cohen & Felson, 1979). Although motivated offenders and victims are important, we are also able to alter the potential for crime by changing the opportunities available in time and space. This knowledge has inspired practical crime prevention partnerships between researchers and police aimed at reducing crime by focusing on places.

The altering of opportunities for crime is done by introducing capable guardians into the situation (Cohen & Felson, 1979). Capable guardians have the power to intervene with the elements of a crime to influence the time-space convergence. The collective of guardians is known generally as controllers and more specifically as offender handlers, victim guardians, and place managers (Cohen & Felson, 1979; Eck, 1994; Felson, 1986). Among each of these three groups, there are varying levels of guardianship (from strongest to weakest): personal, assigned, diffuse, and general (Felson, 1995). An individual with the strongest level of guardianship (personal), such as a parent, friend, or place owner, holds great influence over the elements involved in a potential crime and may have the greatest power to keep crime from occurring. Individuals with general guardianship may include a person simply walking on the street who happens to notice a potential offender watching for targets. A goal of many crime prevention efforts is to increase the levels of guardianship (from weak to strong) in criminogenic places to allow for better prevention of crime (Felson, 1995). In this distribution, the police may act in all roles or none. The ultimate goal is for the police to have less responsibility over crime situations where others may provide stronger levels of guardianship (Scott, 2005).

In the study of crime and place, how place is defined will influence responses to crime at that place and who can be leveraged as a place manager. Within environmental criminology, the study of places largely focuses on areas that are smaller than cities. Such areas may include the easily defined census block or the more nebulous neighborhood. Smaller places, often called micro places, include street blocks, intersections, and addresses, but may be as small as the space around an ATM machine or a parking spot (Eck & Weisburd, 1995).

Attention to micro places increased in the 1990s as data on places became more readily available and desktop GIS tools allowed both police and researchers to more easily examine those units (Eck & Weisburd, 1995). Attention was also boosted by ground-breaking research demonstrating that approximately three percent of addresses and intersections in the city of Milwaukee were responsible for over 50% of the calls for service in the city during a one-year period (Sherman et al., 1989). These places were identified as hot spots of crime. Subsequent research has not only confirmed the presence of this skewed distribution of crime at places but has further identified that hot spots are also stable over time (Andresen & Malleson, 2011; Braga, Papachristos & Hureau, 2010; Groff, Weisburd, & Yang, 2010; Spelman, 1995; Taylor, 1999; Weisburd et al., 2004).

Subsequently, in the early 2000s, there was a growing interest in research on hot spots because of the great potential for practical application within police departments (Weisburd & Braga, 2006; see also Braga, Papachristos, & Hureau, 2014). Extensive research has shown that crime prevention efforts undertaken at hot spots are effective at reducing crime (Braga, 2001; 2005; Braga & Bond, 2008; Braga et al., 2014; Braga & Weisburd, 2010; Weisburd & Braga, 2006). However, the interventions that are taken to respond to hot spots will vary at different units of analysis (Eck, 2005). Further, the expectations of different types of guardians will also vary (Clarke & Eck, 2005). For example, efforts undertaken to respond to hot spots at the street segment level (also known as hot lines) may use a scheme that increases the number, duration, or type of police patrols in the location to disrupt regularly scheduled criminal activity (Sherman & Rogan, 1995; Sherman & Weisburd,
of crime, the team found that the rates of change over time, changes in crime can be better understood. Weisburd and colleagues (2004) found that these street segments have the greatest impact on time. Weisburd and colleagues (2004) concern regarding potential errors developed from miscoding addresses in data. Although there may always be the chance for data entry error, this potential has been reduced over the past decade as records management systems have become more sophisticated and address confirmation has become more common among U.S. police departments. Additionally, both police management and crime analysis units have become more concerned with accurately reporting addresses (and cleaning data).

Group-Based Trajectory Modeling

Within criminal justice, research using group-based trajectory modeling was pioneered by Nagin and Land (1993) and further developed by Nagin (1999, 2005). Group-based trajectory modeling was initially used to examine the trajectories of different groups of people, typically offenders, over time. There are a finite number of general offending paths that one might take over the life course. The modeling process aims to group individuals based on their patterns of offending and desistance over time. These models can then be examined to identify general trends in offending. The trajectory patterns are typically defined as stable (which can be at varying levels: no offending, low offending, high offending), variable (rising or falling), or a combination of the two (e.g., low-rising).

Place-Based, Group-Based Trajectory Modeling

The application of group-based trajectory models to places was first undertaken by Weisburd et al. (2004). Through a series of studies, this work has focused on examining the trajectories of street segments in Seattle around the turn of the century (Groff, 2005; Groff, Weisburd, & Morris, 2009; Groff et al., 2010, Weisburd et al., 2004). The Seattle studies documented the relative stability of crime at one type of micro place, the street segment, over time (Weisburd et al., 2004). The authors argued that if most street segments did not have stable trajectories of crime then the study of hot spots would be less important than theory suggested. Their findings confirmed the stability of crime at hot spots, with 84% of the street segments falling into one of several stable trajectories. They also found, however, that there are a small number of street segments that have sharply rising or falling crime patterns over time. Weisburd and colleagues (2004) found that these street segments have the greatest impact on crime trends in a city; by focusing on what is happening at this small proportion of street segments over time, changes in crime can be better understood.

Further supporting their examination of the stability of crime, the team found that the rates of change (whether positive or negative) were also stable over time. Ongoing research in Seattle led by Groff continued to support these findings (Groff, 2005; Groff et al., 2009; Groff et al., 2010; Weisburd et al., 2004) confirmed the stability of hot spots over time at the street segment level, thus supporting the previous research findings in hot spots policing experiments (Braga, 2001; 2005; Braga & Bond, 2008; Braga et al., 2014; Braga & Weisburd, 2010; Weisburd & Braga, 2006). In further examining hot spots, however, researchers have found that even in high crime neighborhoods there are low (and no) crime addresses (Sherman et al., 1989). Using the data from Seattle, Groff et al. (2010) examined whether this finding stands when examining the trajectories of street segments in hot spots. Groff et al. (2010) asked a useful question: are hot spots uniformly hot? They found that adjacent street segments do not necessarily share the same temporal trajectory of crime. There are “varying degrees of heterogeneity in street to street temporal crime trajectories” (Groff et al., 2010, p. 23). Some areas of Seattle were characterized by homogeneity in temporal crime trends, while in others, there were very different temporal patterns for street segments that were proximal to one another. These findings are also supported by earlier research focused specifically on juvenile crime in Seattle (Groff, 2005; Groff et al., 2009).

To date, the primary unit of analysis examined in the small field of place-based, group-based trajectory models has been street segment (however, see also Griffiths & Chavez, 2004, and Stults, 2010, for examinations of the influence of neighborhood [census tract] trajectories on homicide rates). The current analysis uses a smaller unit of aggregation than previous studies that have combined temporal and spatial trends: the street address. Smaller units of analysis are particularly interesting to investigate in light of the findings by Groff and colleague (2009) and Groff et al. (2010), both of whom suggest that aggregation may hide important variations in the data. We acknowledge Weisburd and colleagues’ (2004) concern regarding potential errors developed from miscoding addresses in data. Although there may always be the chance for data entry error, this potential has been reduced over the past decade as records management systems have become more sophisticated and address confirmation has become more common among U.S. police departments. Additionally, both police management and crime analysis units have become more concerned with accurately reporting addresses (and cleaning data).
because of regular reporting and analysis of crime data through COMPSTAT style programs.

Place-based researchers often work with a police or community partner to translate their research into action. If place-based research is to guide practice, then it could also be important to use the smallest unit of analysis possible to have the most direct impact on crime levels. Indeed, the original research on hot spots was focused on addresses and intersections (Sherman et al., 1989). Further, based on the finding by Groff et al. (2010) that while hot spots remain hot over time, they are not necessarily surrounded by other hot locations, it is possible that a few hot dots within that street segment are driving those results (Eck & Eck, 2012). Thus, focusing on addresses provides two potential efficiencies for practical application. First, fewer resources may be used by police, in general, when focusing on the small proportion of crime-ridden addresses rather than larger geographic areas (Eck, Clarke, & Guerette, 2007; Goldstein, 1990). And second, address level interventions may also focus on transferring responsibilities for crime at places from the police to place managers (Eck & Eck, 2012; Eck & Guerette, 2012).

Like previous studies that have examined group-based trajectories of crime at places and spatial relationships, we use a sequential approach to our analysis. We begin by describing the Cincinnati city-wide crime trend during the study period, 1998-2012. Next, we report results of group-based trajectory modeling at the street address level. Finally, we describe spatial relationships, using the trajectory as the dependent variable. The results are examined city-wide, and then one specific high-crime neighborhood is highlighted. We use a variety of tools for this, most notably Stata 14 and ArcGIS 10.3.

**Crime Data Description**

The Cincinnati Police Department provided police incident data for the years 1998-2012. The police incident data that we use includes both citizen calls for service and officer-initiated activities. The incident type and location are updated as officers arrive on the scene, reducing (but not eliminating) the potential for classification and location error found in raw calls for service data noted by previous studies (Klinger & Bridges, 1997).

Our aim is to describe the development of crime and disorder at addresses. Data were initially provided for 4,350,130 incidents, including incidents outside of Cincinnati. Incidents were geocoded with ArcGIS 10.3 using a composite geolocator comprised of address point, parcel, and street centerline base data provided by the Cincinnati Area Geographic Information System (CAGIS). Incident data were clipped to Cincinnati city limits, and locations that were not locatable were dropped (this resulted in dropping 378,983 incidents). We further dropped incidents with recorded locations at police stations (69,895 incidents), hospitals (18,133 incidents), and courthouses and City Hall (6,324 incidents). In practice, these locations are often recorded when the incident location is not available. We also dropped incidents that are unrelated to crime and disorder problems: traffic incidents; parking issues; prisoner transports; and service calls, such as assistance to the fire department, medical emergencies, and suicide attempts (1,292,368 incidents). Incidents at street intersections were also excluded (336,676 incidents), because they are not attributable to an address with an identifiable owner with responsibility for the address. Weisburd and colleagues (2004) similarly removed incidents at intersections from their analysis.

What remained were 2,247,751 police incidents in Cincinnati from 1998-2012 that were related to crime and disorder at an identifiable address. Over the 1998-2012 period, the total number of incidents per year fell from 142,743 to 140,472, a decrease of 1.6%. These incidents were then classified by the researchers as disorder,1 property,2 or violent.3 City wide trends for each of these incident types is shown in Figure 1. Overall, however, the trend across all three crime types is largely one of stability—to the extent there have been city-wide changes, those changes are minor.

The 2.2 million police incidents occurred at 125,226 unique addresses across the entire time period. In any given year, the number of addresses at which incidents occurred varied between 37,679 and 42,350. In 2012, there were 125,556 address points in the Cincinnati Area Geographic Information Systems address point layer, suggesting that most addresses in Cincinnati are included in our analysis. An address must have had at least one police incident during the 1998-2012 period to be included in this analysis. Addresses did not need to have an incident in every year to be included. In fact, only about one third of addresses in our data had one or more police incidents in any given year in our data. This demonstrates how rare police incidents are at the address-level. Even in a data set comprised only of addresses that have had crime at one time, the majority of addresses simply do not produce crime in any given year.

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1. disorder
2. property
3. violent
Analytic Strategy: Trajectory Analysis

Group-based trajectory models were estimated with Stata 14 and the user-written command *traj* (Jones, 2015) using zero-inflated Poisson models of the count of police incidents per year at each address. Counts were truncated at the 99th percentile, 16 incidents, to facilitate model estimation, in a manner similar to Weisburd and colleagues (2004). The primary model specification question for any trajectory analysis is how many trajectories to include. The order of the polynomial that describes the trend of each group of places is of secondary concern (Nagin, 2005). Selecting the number of trajectories starts by examining the change in the Bayesian Information Criterion (BIC) as additional trajectories are added to the model. This is the approach used by previous trajectory of crime at place studies (Groff et al., 2010; Weisburd et al., 2004). However, this approach has limitations. We estimated models with up to 20 trajectories for each crime type. With every additional trajectory, the BIC improved. Visual inspection of plots from these models suggested considerable overlap in these trajectories, with very small percentages of places in most trajectories.

BIC, however, is only a first consideration in identifying group-based trends. Nagin (2005) and Nagin and Tremblay (2005) suggest not being shackled to a single statistic when selecting models. Model selection is as much art as science—all models are an abstraction of reality, and there is no truly correct model. Nagin (2005) explicitly cautions against including trajectories that do not add to understanding the data: the “objective is not to identify the ‘true’ number of groups” (p. 173) but instead to identify the most parsimonious model that describes features of the population. Stated differently, trajectories should be helpful in distinguishing groups of places from one another. Additional trajectories should not be added after it becomes difficult to distinguish different trajectories from one another. We, therefore, relied on visual inspection of estimated trajectory plots combined with other diagnostics instead of BIC alone when selecting our base models. We agree with Nagin (2005) that parsimony is a valuable goal, and we considered whether each additional trajectory revealed something new about the population rather than whether each additional trajectory marginally improved a model fit statistic.
The Trajectories of Crime at Addresses in Cincinnati, 1998-2012

Model Estimates

With our Cincinnati dataset, six trajectories adequately captured the variation in the trajectory of each crime type without duplicating similar trajectories. We acknowledge that other modelers may choose differently, with slightly different results, even with the same data. Model plausibility was confirmed with diagnostics suggested by Nagin (2005), which are shown with the percentage of addresses in each trajectory in Table 1. The average posterior probability of group assignment, odds of correct classifications, and comparisons of model group assignment compared to group assignment using the maximum posterior probability rule were all well within guidelines suggested by Nagin (2005) for the six-trajectory model. Models with more trajectories generally performed poorly on one or more of these diagnostics. Models with more than 12 trajectories had serious problems with posterior probabilities despite an improvement in BIC, suggesting that those models had more difficulty assigning addresses to trajectory groups than the six-trajectory model described below. A plot of the estimated trajectories appears below as Figure 2.

Figure 2: Estimated Trajectories of Crime at Addresses in Cincinnati, 1998-2012

As shown in Figure 2, the majority of addresses have low-stable levels of crime (58.3% of all addresses, trajectory 2, symbolized by an open circle). Crime at these addresses is so low as to be considered zero; these are places at which the average number of crimes ranges from 0.150 to 0.191 per year. This is contrasted with the high-stable crime trajectory, which comprises 2.5% of addresses
(symbolized by a filled square). The average number of crimes at these addresses is an order of magnitude greater than that of the low-stable crime trajectory, averaging between 14.175 and 20.033 per year. (These averages are calculated using the original, non-truncated data; see endnote 4 for further discussion of these calculations).

Two groups experienced declining crime during the study period. Trajectory 4 (12.3% of addresses, solid diamond) and trajectory 5 (3.6%, open diamond) show similar trends although trajectory 5 experienced a higher magnitude of crime than trajectory 4 throughout the study period. Trajectory 1 (16.7%, open triangle) and trajectory 3 (6.6%, solid triangle) both increased in crime during the study period. These two trajectories show similar patterns of increase, with trajectory 3 having higher crime throughout the study period.

Characteristics of the Six Trajectories

Unlike studies using Seattle data (Groff, 2005; Groff et al., 2009; Groff et al., 2010; Weisburd et al., 2004), there were not large city-wide changes in Cincinnati crime counts during our study period—the 2012 total crime count in Cincinnati was 1.6% lower than the 1998 total crime count. Like the Seattle studies, however, we do find substantial changes in the number of crimes occurring at places within each trajectory group. Substantial crime increases in the increasing trajectories were offset by decreases at places in the declining trajectories. Table 1 shows the percent of addresses by trajectory group along with the percent of crime occurring within each trajectory in 1998 and 2012. Figure 3 is an area chart showing how the proportion of crime that occurred within each trajectory trend group changed over time. In 1998, 5.8% of all crimes occurred at places assigned to trajectory 1. By 2012, 19.2% of crime occurred at places assigned to this increasing trajectory. The high-stable crime trajectory 6 comprises 2.5% of addresses—yet about one-third of crime occurs at places assigned to this trajectory regardless of year. Much in the same way that national crime statistics do not necessarily represent the trends in any given city, the small city-wide difference in the total crime count from 1998 to 2012 obscured large crime changes within trajectories.

Land Use Varied by Trajectory

Table 2 shows the percent of selected land use types by trajectory. Across all trajectories, the most common land use type is residential: 62.3% of all addresses in the data are residential. Residential land use includes single-family, two-family, and three-family dwellings, as well as apartments. Even among addresses in the high-stable crime group, trajectory 6, residential is the most common land use category. Retail establishments comprise a larger proportion of the high-crime group (18.1%) than of other groups—but 10.76% of medium-declining (trajectory 5) were retail as well.

Table 1: Percent of City-Wide Addresses within Trajectory Group and Diagnostic Criteria

<table>
<thead>
<tr>
<th>Trajectory Group</th>
<th>( \hat{P} ) (%)</th>
<th>( P_f ) (%)</th>
<th>Ave. PP</th>
<th>Odds correct classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16.701</td>
<td>16.373</td>
<td>0.901</td>
<td>45.600</td>
</tr>
<tr>
<td>2</td>
<td>58.270</td>
<td>58.735</td>
<td>0.976</td>
<td>28.794</td>
</tr>
<tr>
<td>3</td>
<td>6.628</td>
<td>6.618</td>
<td>0.948</td>
<td>257.905</td>
</tr>
<tr>
<td>4</td>
<td>12.250</td>
<td>12.142</td>
<td>0.919</td>
<td>81.758</td>
</tr>
<tr>
<td>5</td>
<td>3.639</td>
<td>3.621</td>
<td>0.957</td>
<td>582.605</td>
</tr>
<tr>
<td>6</td>
<td>2.511</td>
<td>2.511</td>
<td>0.990</td>
<td>3,831.700</td>
</tr>
</tbody>
</table>

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Figure 3: Count of Crimes by Trajectory Trend Group, Cincinnati, 1998-2012

Table 2: Land Use by Trajectory (Percent within Each Trajectory)

<table>
<thead>
<tr>
<th>Trajectory Group</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial</td>
<td>1.1</td>
<td>0.8</td>
<td>2.4</td>
<td>1.6</td>
<td>4.8</td>
<td>5.8</td>
<td>1.3</td>
</tr>
<tr>
<td>Government-owned</td>
<td>0.8</td>
<td>5.3</td>
<td>1.4</td>
<td>1.5</td>
<td>2.3</td>
<td>3.8</td>
<td>3.7</td>
</tr>
<tr>
<td>Industrial</td>
<td>1.0</td>
<td>0.8</td>
<td>1.9</td>
<td>1.7</td>
<td>3.9</td>
<td>0.9</td>
<td>1.2</td>
</tr>
<tr>
<td>Parking</td>
<td>0.4</td>
<td>0.8</td>
<td>0.6</td>
<td>0.7</td>
<td>1.4</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>Retail</td>
<td>2.5</td>
<td>1.5</td>
<td>6.2</td>
<td>3.7</td>
<td>10.8</td>
<td>18.1</td>
<td>3.0</td>
</tr>
<tr>
<td>School</td>
<td>0.2</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.6</td>
<td>2.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Vacant</td>
<td>1.6</td>
<td>4.5</td>
<td>1.8</td>
<td>5.1</td>
<td>5.2</td>
<td>2.3</td>
<td>3.9</td>
</tr>
<tr>
<td>Residential</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apartments 4-19 units</td>
<td>5.7</td>
<td>1.5</td>
<td>15.4</td>
<td>4.8</td>
<td>12.9</td>
<td>20.0</td>
<td>4.4</td>
</tr>
<tr>
<td>Apartments 20-39 unit</td>
<td>0.5</td>
<td>0.4</td>
<td>2.2</td>
<td>0.5</td>
<td>1.8</td>
<td>9.3</td>
<td>0.8</td>
</tr>
<tr>
<td>Apartments 40+ units</td>
<td>4.5</td>
<td>2.3</td>
<td>7.0</td>
<td>3.4</td>
<td>4.5</td>
<td>16.3</td>
<td>3.5</td>
</tr>
<tr>
<td>Single-family dwelling</td>
<td>56.4</td>
<td>39.7</td>
<td>27.5</td>
<td>47.3</td>
<td>16.9</td>
<td>2.3</td>
<td>40.8</td>
</tr>
<tr>
<td>Two-family dwelling</td>
<td>12.1</td>
<td>5.3</td>
<td>14.2</td>
<td>11.5</td>
<td>10.9</td>
<td>2.5</td>
<td>7.9</td>
</tr>
<tr>
<td>Three-family dwelling</td>
<td>2.3</td>
<td>0.8</td>
<td>4.3</td>
<td>2.5</td>
<td>4.2</td>
<td>1.5</td>
<td>1.6</td>
</tr>
<tr>
<td>Other residential</td>
<td>5.2</td>
<td>1.5</td>
<td>8.0</td>
<td>6.3</td>
<td>6.1</td>
<td>3.2</td>
<td>3.3</td>
</tr>
<tr>
<td>Other</td>
<td>5.9</td>
<td>34.5</td>
<td>7.0</td>
<td>9.1</td>
<td>13.8</td>
<td>10.9</td>
<td>23.6</td>
</tr>
<tr>
<td>Total</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>
Crime Types Varied by Trajectory

The mix of crime types varied by trajectory as well. Like previous scholars, we were unable to estimate separate trajectory models by crime type due to the relatively rare nature of crime across time and space. We can, however, examine broad categories of crime within each trajectory after model estimation. Figure 4 shows the percentage of police incidents that were property, violent, or disorder. As expected, disorder is more common than both property and violent crime in all trajectories. The high-stable trajectory and one of the declining trajectories (trajectory 5) shows more violent incidents than property incidents. The low-stable crime trajectory had the highest proportion of property crime and lowest proportion of violence compared to disorder among the trajectories.

Figure 4: Percent of Property, Violent, and Disorder Incidents by Trajectory

Spatial Relationships of Trajectories and Confirmation of Risky Facilities

We examined spatial relationships using ArcGIS 10.3. Like Groff and colleagues (2010), we used Ripley’s K to assess the degree of spatial clustering of the various trajectories. Ripley’s K compares the clustering of observed points to complete spatial randomness (CSR) at multiple distances. Because addresses are not distributed completely at random, we also compared the modeled trajectories to that of all addresses in Cincinnati. Ripley’s K results (available upon request) show that all trajectories are more clustered than CSR up to a distance of about one-half mile. The high-stable crime trajectory (6) shows greater spatial clustering than other trajectories. The low-stable crime trajectory (2) shows similar clustering to that of all addresses. The remaining trajectories fell in between these two extremes.

In Figure 5, we examine the clustering of high-stable crime places (trajectory 6) by neighborhood in Cincinnati. The thematic map in Figure 5 compliments Figure 6, which shows a hot spot map of high-stable crime addresses (i.e., addresses in trajectory 6). As expected, the figures show that high-stable crime addresses are not uniformly distributed across Cincinnati. These figures also show that the crime concentration is likely due to the relatively higher concentration of high-crime addresses in particular neighborhoods. The inset in Figure 6 highlights the Cincinnati neighborhood of Over-the-Rhine, a neighborhood that is wholly contained within a hot spot of high-stable crime addresses when traditional mapping methods are used.
Figure 5: Percent of Addresses in the High-Crime Group (Trajectory 6) by Neighborhood, Cincinnati

Figure 6: Hot Spot High-Stable Crime (Trajectory 6) Addresses, Cincinnati, with Inset of Over-the-Rhine
Both Figure 5 and Figure 6 aggregate data to an aerial unit (neighborhood for Figure 5, 250-foot grid cell for Figure 6). These figures suggest that the entire neighborhood of Over-the-Rhine should be an area of focus for crime prevention efforts. This neighborhood is 0.5% of the total area of Cincinnati, yet 9.8% of high-stable crime addresses are in Over-the-Rhine (see inset, Figure 6). In fact, the entire neighborhood is covered by a hot spot of high-stable crime addresses.

Larger scale maps (i.e., more “zoomed in”), however, tell a different story. Prior research of crime at place has found that within each type of facility type, a relative handful of places are problematic while the remainder are not (Eck et al., 2007). We choose one facility type, apartments, to illustrate the risky facilities hypothesis over time in our data. This facility type also allows some exploration of density, since land use classifications include an ordinal scale of the number of units (4-19 units, 20-39 units, and 40+ units) in apartment buildings. Figure 7 shows high-stable crime (trajectory 6) and low-stable crime (trajectory 2) apartments by number of units in a small area of Over-the-Rhine, the neighborhood which appears to be wholly contained within a hot spot of high-stable crime addresses.

Figure 7: High-Stable Crime and Low-Stable Crime Places in Over-the-Rhine, Cincinnati

Figure 7 shows what Figures 5 and 6 cannot—he distance from any high-stable crime place to a low-stable crime place is typically short. Many high-stable crime addresses share a street segment with similarly-sized low-stable crime places. The small area shown in Figure 7 is representative of other areas in Over-the-Rhine. Within Over-the-Rhine, nearly four out of five high-stable crime apartment buildings are within one block of a similarly-sized low-stable crime apartment building (83 of the 106 high-stable crime apartment buildings are within 250 feet of a low-stable crime apartment building). Another 18.9% of high-stable apartment buildings are within two blocks of a low-stable crime building (20 addresses). Just three high-stable crime apartment buildings are more than two blocks from a similarly-sized low-crime apartment building in Over-the-Rhine.
It is clear that places with very different developmental trajectories coexist within the same neighborhood and within the same street segment. Although our focus on places within the high-stable crime trajectory pointed us to the Over-the-Rhine neighborhood for potential interventions, it is not true that every address in the neighborhood is high-crime. It is also not true that every high-crime street segment is uniformly high in crime. High-stable crime, low-stable crime, increasing-crime, and decreasing-crime places all coexist in very close proximity to one another, even when the scope of the analysis is limited to a single facility type. Therefore, while our initial analysis suggested that the Over-the-Rhine neighborhood was potentially in need of a massive intervention, our more detailed analysis demonstrated that such an effort might not be either necessary or effective. Instead, it is likely useful to examine individual problem places, specifically those in the high-stable crime trajectory, to prioritize individualized responses.

Conclusion

We used group-based trajectory models to describe crime at the address-level with 1998-2012 data from the Cincinnati Police Department. We found that six trajectories adequately described the data. Like previous research that examined trajectories at the street segment level (e.g. Groff et al., 2010; Weisburd et al., 2004), we found that city-wide trends were driven by changes in a minority of these trajectories. Using address-level data allowed us to explore land use. We found that land use varied by crime trajectory, but residential purposes were most common in all trajectories. However, places in the high-crime trajectory were more likely to be retail than places in other trajectories. While we were unable to model different crime types separately, we did examine crime types after model estimation. Disorder was the most likely incident type across all trajectories; however, violent crime was more likely in the high-stable crime trajectory than at other trajectories.

Spatially, like Groff and colleagues (2010), we find that each trajectory is more clustered than would be assumed under alternative models of complete spatial randomness and more clustered than addresses in general. Also like Groff and colleagues (2010), we find that this clustering can be misleading. Groff and colleagues (2010) use a quantitative method (bivariate Ripley’s K); we use a more visual method. The results are similar regardless of method. Places of differing trajectories coexist within very short distances of each other despite being more clustered than would be expected at random.

This finding can be re-stated simply: High-stable crime places exist on the same street segment as low-stable crime, increasing-crime, and decreasing-crime places. This suggests that many of the processes generating crime could occur at a smaller unit of aggregation than street segment. This also suggests that police and community responses to hot spots of crime should be tailored to where the crime is actually occurring, whether it is an entire street with multiple addresses that are crimogenic or if one or two addresses are driving the heat. Further, by identifying the differences in guardianship between the high crime and the low (or no) crime addresses, recommendations for improvement can be made to place managers and other controllers at high-crime places. Although it is possible that some high-crime places are just more popular than low-crime places near them (c.f., Wilcox & Eck, 2011), this is unlikely to be true for all high-crime places. The implication for research is a need to revisit address as a unit of useful analysis, much as Sherman and colleagues (1989) used.

Our methods have limitations. First, we acknowledge that measurement error may be an issue at the address level when using police data. Given the utility of location information for modern police operations, however, we suspect that incident-level data such as we use here have less error today than in the past. Still, it is possible that police dispatchers and/or officers make errors when recording addresses. It is also possible that our geocoding process introduced some unknown degree of error. Like previous researchers using trajectory models at places, we were forced to truncate the data at the 99th percentile, limiting our ability to discuss changes within the high-stable crime trajectory (see endnote 4). Like previous researchers, we are also unable to run crime-specific models due to the relative rareness of crime.

Another limitation has interesting implications: We lack measures of crime within each address. Prior work has found that crime is concentrated among a relative handful of cities within a state, a relative handful of neighborhoods within a city, and a relative handful of street segments within a neighborhood. Like prior work, we find that crime is concentrated at a relative handful of addresses. Yet our unit of analysis is not as granular as it could be. Most addresses have further divisions of both theoretical and practical importance. Apartment addresses, for example, have several dwelling units. Retail addresses may contain stores of different types, and each store may have subunits of interest (front counter versus back storeroom, for example). Even single-family dwelling addresses have subunits (front yard, back yard, garage, interior, etc.). So far,
every time researchers have used smaller units of analysis, a key finding has been that crime is more concentrated than at larger units of analysis. It is very likely that if we had sub-address data, we would find that crime is concentrated at even smaller units of analysis. This information would help to further tailor responses to crime. There is a limit to the practical utility of using smaller and smaller units of analysis—but we likely have not yet reached that limit.

Our findings suggest that the place-based processes that cause crime are complex. Since places on the same street segment are often in different trajectories, those processes may be quite different for places that are literally next to each other. We lack measures that could be used to determine those processes in the available retrospective secondary data; however, some measures not available during our study period will be available to future researchers. For example, the Hamilton County, Ohio auditor only recently retained electronic parcel data indefinitely—the practice until 2007 was to keep every third year. Future work could examine the impact of changing land use on crime counts at small units of analysis, for example, using secondary data. Future work should also focus on the impact of guardianship at micro places. What are the differences in management styles and levels at places with high crime versus those with low or no crime? Place management decisions impact how a place is used and by whom (Eck, 1994). Place management decisions shape every element of the built environment, which changes how people use space. While indirect measures of place management could be culled from secondary data (Payne, 2010), secondary data has limits. In order to truly model the developmental trajectory of places, future researchers will likely need to collect primary data regarding place management of places over time. Direct measures of place management such as not just that a place is a bar, but what type of bar it is (Eck, 1994; Madensen & Eck, 2008) should be included. Our findings suggest that these measures should be at as small a unit of analysis as is practical.

Our findings suggest that some addresses should be viewed as hot spots, separate from the macro context within which they exist. Our findings support, for example, regulatory schemes such as those described by Eck and Eck (2012), who suggest regulating crime similarly to pollution. If crime were to be randomly distributed along a street segment, such regulations would be unfair and unlikely to work. Ends-based regulations, such as chronic nuisance ordinances that entice owners to reduce nuisance calls for police service such as noise complaints, can only work if the distribution of crime is non-random at the address level. If localities allow some property owners to externalize the cost of managing their places appropriately to the city in the form of police services, then appropriate place management practices may become a competitive disadvantage. Many municipalities and states have attempted to rebalance the incentive structure for place management using fees and fines for excessive police services. There are few tests of the effectiveness of such fees and fines (Payne, 2015). Our current findings add to the growing evidence that such address-based regulation is a plausible way to reduce crime.

The study of group-based trajectory modeling of places is still in its infancy. Our research supports many of the earlier findings of researchers examining the trajectories of street segments. However, by examining data at the address level, we provide our practitioner colleagues with more discrete targets for their crime prevention efforts. Future efforts should collect more details about the places in high crime trajectories to further aid practical applications.

References


**About the Authors**

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**Endnotes**

1 Disorder included the following Cincinnati Police Department incident types: animal complaint, attempt to locate, automated holdup alarm, aware alarm, complaint of panhandlers, complaint of prostitutes, con game, curfew violation, disorderly group (4 or more), disorderly person (includes crowd), drug use/sale, family trouble (non-violent), holdup alarm (all except sig66), inactivity alarm, jurismonitor alarm, juvenile complaint, mental injured, mentally impaired-nonviolent, mentally impaired-injuries, neighbor trouble, noise complaint, non-resident alarm, non-critical missing, person down and out, person down, not combative, not sick/injured, person screaming, place found open, prowler, resident alarm, suspicious person or auto, telephone harassment, trespasser, unknown trouble.

2 Property incidents included the following Cincinnati Police Department incident types: auto theft just occurred, auto theft report, breaking and entering in progress occupied, breaking and entering in progress unoccupied, breaking and entering report, criminal damage just occurred, criminal damage report, property found, property lost, theft just occurred, theft report, unauthorized use of auto.

3 Violent incidents included the following Cincinnati Police Department incident types: abduction, amber alert, assault just occurred, assault person injured, assault report, assault with injuries, barricaded person, bio/chemical threat, bomb threat, explosive device, child victim, critical missing, cutting has occurred, domestic violence in progress, domestic violence report, fight in progress, hostage situation, menacing just occurred, menacing report,
mental violent, mentally impaired-violent, person cut, person shot, person with gun, person with weapon (includes knife), possible DOA, possible shots fired, rape just occurred, rape person injured, rape report, rape with injuries, robbery just occurred, robbery person injured, robbery report, robbery with injuries, sex offense just occurred (not rape), sex offense report (not rape), shooting has occurred, stalking in progress, stalking report.

4 This is the same solution that Weisburd and colleagues (2004) use when modeling crime at street segments (see their footnote 14). Weisburd and colleagues (2004) then report graphs using the original data, not the truncated data (we display model estimates instead for reasons described in this endnote). Displaying averages based on the original data, as Weisburd and colleagues (2004) do, suggests the transformed data can do something that they cannot do. That is, models of truncated data cannot describe trends among very high crime places.

Conceptually, truncating the data limits the ability of the model to describe changes at extraordinarily high-crime places. It is possible that some places change from very high-crime to merely high crime over time. Truncating the data allows for model estimation, but the models can no longer detect such changes at very high-crime places. We choose to display model estimates using transformed data rather than untransformed data in our graphs for this reason: our models can differentiate between high-crime and other trajectories, but our models cannot detect changes within the high-crime trajectories. When we discuss average crime counts, however, we use the original (i.e. unmodified) scale.

5 Figure 5 shows a hot spot map of high-stable crime addresses in Cincinnati created using Gi* (Getis & Ord, 1992). Gi* is similar to kernel density estimation (KDE) in that it calculates the degree of spatial concentration using the weighted distance to other points. Unlike KDE, Gi* allows for hypothesis testing and has been shown to have better predictive accuracy than KDE (Chainey, 2005, 2010; Ratcliffe & McCullagh, 1999). The size of the fishnet polygon used here was 250 feet.

6 The risky facilities hypothesis is sometimes misinterpreted to mean “some facility types are risky.” This is not what Eck, Clarke, and Guerette (2007) found. Instead, they found that even among facility types that are considered risky (bars, apartments, etc.), it is only some facilities that are risky—that a handful of bars, for example, are problematic while most bars are not.