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Spatiotemporal Crime Patterns Across Six U.S. Cities: Analyzing Stability and Change in Clusters and Outliers

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Abstract

Objectives Examine the degree of crime concentration at micro-places across six large cities, the spatial clustering of high and low crime micro-places within cities, the presence of outliers within those clusters, and extent to which there is stability and change in micro-place classification over time.

Methods Using crime incident data gathered from six U.S. municipal police departments (Chicago, Los Angeles, New York City, Philadelphia, San Antonio, and Seattle) and aggregated to the street segment, Local Moran's I is calculated to identify statistically significant high and low crime clusters across each city and outliers within those clusters that differ significantly from their local spatial neighbors.

Results Within cities, the proportion of segments that are like their neighbors and fall within a statistically significant high or low crime cluster are relatively stable over time. For all cities, the largest proportion of street segments fell into the same classification over time (47.5% to 69.3%); changing segments were less common (4.7% to 20.5%). Changing clusters (i.e., segments that fell into both low and high clusters during the study) were rare. Outliers in each city reveal statistically significant street-to-street variability.

Conclusions The findings revealed similarities across cities, including considerable stability over time in segment classification. There were also cross-city differences that warrant further investigation, such as varying levels of spatial clustering. Understanding stable and changing clusters and outliers offers an opportunity for future research to explore the mechanisms that shape a city's spatiotemporal crime patterns to inform strategic resource allocation at smaller spatial scales.

Keywords Micro-places · Spatiotemporal crime patterns · Spatial clusters · Spatial outliers

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Introduction

Criminology has seen considerable growth in the study of crime and place over the past few decades, with findings challenging the implicit assumption that crime is uniformly distributed within neighborhoods (Sherman et al. 1989; Weisburd et al. 2012; Lee et al. 2017). Much of the work in this area has focused on the distribution of crime across micro spatial units (e.g., addresses, intersections, street segments, blockfaces, businesses) and the extent to which such units display stability over time. Findings suggest that a relatively large percentage of all crime within a city can be found at a relatively small proportion of micro-places, and that while micro-places tend to display stable crime levels over time, change in crime at relatively few places can affect citywide crime levels (e.g., Weisburd et al. 2004; Braga et al. 2010; Groff et al. 2010; Curman et al. 2015; Andresen et al. 2017).

Given the well-established finding that crime tends to concentrate at relatively few micro-places within a city, additional work has begun to consider the spatial relationships among these micro-places. Criminological theory and research suggest the mechanisms that produce such patterning can operate across different spatial scales, with *both* micro-place features *and* meso-level (e.g., neighborhood) characteristics contributing to crime risk (e.g., Wilcox and Tillyer 2018; Jones and Pridemore 2019; Tillyer et al., 2021; O'Brien et al. 2022). This is consistent with two reported spatial findings related to the distribution of micro-places within cities. First, there is considerable *within*-neighborhood variability in crime, with high crime and low crime places often adjacent to one another (e.g., Sherman et al. 1989; Groff et al. 2010; O'Brien and Winship 2017). Second, despite observed street-to-street variability, there remains evidence that some places with similar crime trajectories tend to cluster (Groff et al. 2010; Wheeler et al. 2016) and that year-to-year persistence in crime and disorder levels are observed at both street *and* neighborhood levels (O'Brien and Winship 2017). With few exceptions (e.g., Hipp and Kim 2017), these relationships have been explored within single city studies that often examine different time periods with varying methods, somewhat limiting cross-city comparisons.

The present study uses data from six unique urban landscapes–Chicago, Los Angeles, New York City, Philadelphia, San Antonio, and Seattle–to build on existing crime and place research. We explore additional dimensions of spatiotemporal crime patterns, examining the extent to which micro-places are similar to and different from their local spatial neighbors, and stability and change in these relationships over time. Specifically, the purpose of the present study is twofold. First, we are interested in the spatial distribution of micro-places across each city, with a focus on examining both the clustering of high and low crime street segments *and* street-to-street variability in crime in a given year. We do this by identifying statistically significant high and low crime clusters of street segments and outliers within those clusters that differ significantly from their local spatial neighbors. This allows us to observe the non-random spatial patterning of crime across micro-places within a city *and* the degree of similarity and dissimilarity among local spatial neighbors in a given year within a city. Second, we explore stability and change over time in the clustering of high and low crime street segments within a city *and* similarity and/or dissimilarity among spatial neighbors. In other words, to what extent does the location of a city's high and low crime clusters–and outliers within those clusters–change over time? We do this by examining within-segment variation in cluster-outlier classification over the course of the study for each city. The findings offer directions for crime prevention, theory, and future research.

Distribution of Crime at Micro-Places

There is a sizable body of research demonstrating that crime is not randomly distributed across space; rather, it tends to concentrate at relatively few micro-places, or *hot spots* (Sherman et al. 1989; Eck et al. 2000; Weisburd et al. 2004; Braga et al. 2010, 2011; Gill et al. 2017; Lee et al. 2017; Tillyer and Walter 2019; O'Brien 2019). Weisburd has called this phenomenon the *law of crime concentration*, which states that "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentage for a defined cumulative proportion of crime" (2015:138). For example, Sherman et al. (1989), report that over half of all calls for service to the police in Minneapolis were linked to just 3.3% of the city's addresses and intersections.

Some studies from other cities document similar distributions of crime incidents across micro-places. For example, 4.5% of street segments accounted for approximately half of all crimes from 1989 to 2002 in Seattle (Weisburd et al. 2004).[1] Research examining crime in Boston over a 29-year period reveals that less than 3% of street segments and intersections generated more than half of all gun assault incidents, while 5% of street segments and intersections generated approximately two-thirds of all robberies (Braga et al. 2010, 2011). Similarly, about 5% of street blocks in Vancouver, BC accounted for half of all crimes from 1991 to 2006 (Curman et al. 2015). In Tel Aviv-Jaffa, Israel, approximately 4.5% of street segments accounted for about half of all crimes in 2010 (Weisburd and Amram 2014).

Additional research has highlighted some variation in the degree of concentration by city size and crime type. For example, in Brooklyn Park, a small suburban city outside of Minneapolis, just 2% of street segments generated half of all crimes from 2000 to 2014 (Gill et al. 2017). Andresen and Malleson (2011) examined the percentage of street segments that accounted for 50% of various crime types in Vancouver, Canada in 1991, 1996, and 2001. Less than 1% of street segments produced 50% of the robberies, while approximately 6% of street segments accounted for 50% of auto thefts and 8% of street segments accounted for 50% of burglaries. In Seattle, juvenile arrests from 1989 to 2002 were highly concentrated among street segments, with 50% of arrest incidents in a given year occurring at less than 1% of street segments (Weisburd et al. 2009). In St. Louis, 5% of street segments accounted for an average 54.7% of violent crimes annually from 2000 to 2014, and approximately 39.1% of property crime during that same period (Levin et al. 2017). Favarin (2018) reports that from 2007 to 2013, on average 4% of street segment in Milan accounted for 50% of burglaries in a given year, while an average of 1.6% of street segments accounted for 50% of robberies in a given year. Alternatively, Hipp and Kim (2017) examined the percentage of a city's crime generated by the top 5% of street segments in 42 southern California cities. While notable crime concentration was present across all cities, the level of concentration varied considerably (Hipp and Kim 2017).

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[1] If a segment had addresses with ranges greater than 100, Weisburd et al. (2004) created multiple segments defined by "hundred blocks." For example, they created three segments for a street with house addresses ranging from 1 to 299.

Temporal Crime Trends at Micro-Places

Additional research on crime and place has examined temporal stability in crime at micro-places. One of the most important implications stemming from this area of research is that a small proportion of microgeographic places can have a sizable impact on citywide crime rates. In Weisburd et al.'s (2004) study of crime in Seattle, for example, crime levels at most street segments were stable over time, though drastic changes at relatively few street segments affected city-level crime trends, driving the overall decline in crime during the study period. Specifically, Weisburd and colleagues used group-based trajectory analysis to identify 18 unique crime trajectories among Seattle's street segments from 1989 to 2002, which they further classified into stable, increasing, and decreasing categories to summarize observed variation in stability and change at street segments over time. Eight of the eighteen original trajectories (representing 84% of all segments) were classified as stable; seven trajectories (representing 14% of street segments) were classified as decreasing; and three trajectories (representing approximately 2% of street segments) were classified as increasing over the study period. As Weisburd et al. (2004: 300) note, "This suggests that most of the street segments in the city did not follow the general crime decline found in Seattle as a whole" over the course of the study. Similarly, in their analysis of juvenile arrest incidents in Seattle from 1989 to 2002, Weisburd and colleagues (2009) found volatility in a small proportion of street segments citywide. Specifically, they report that nearly 89% of segments fell into a low-crime stable trajectory that accounted for only 12% of juvenile arrest incidents over the course of the study, while just 0.29% of segments fell into higher crime trajectory groups that accounted for approximately one third of all arrest incidents.

Studies examining micro-level crime changes over time in other cities reveal some cross-city variability in micro-place crime trajectories (e.g., Braga et al. 2010, 2011; Curman et al. 2015; Andresen et al. 2017). Similar to Weisburd et al.'s (2004) findings in Seattle, Braga and colleagues (2010, 2011) report that micro-level gun assault and robbery trends in Boston from 1980 to 2008 were driven by changes at relatively few microgeographic places. Curman et al. (2015) examined calls for service reports across Vancouver, B.C. street segments from 1991 to 2006, identifying seven crime trajectories, one of which was classified as stable (representing 70% of streets) and six of which displayed declines in crime during the study period (representing 30% of streets). Relative to Seattle, a greater percentage of streets contributed to the observed citywide crime declines in Vancouver during the study period, though declines at high crime segments played a large role in driving crime down.

Wheeler et al. (2016) offer a replication of Weisburd et al. (2004) and Curman et al. (2015). Examining crime trajectories across street segments in Albany from 2000 to 2013, they report eight trajectory groups. Similar to the results observed in Vancouver (Curman et al. 2015), none of the eight trajectory groups in Albany displayed increases in crime during the study period. Instead, the trajectory groups largely mirrored overall decreases in citywide crime and were distinguished by their mean crime levels, with more than 40% of street segments falling into trajectory groups with crime counts decreasing an average of 35% during the study period (Wheeler et al. 2016).

Additional methods have been used to examine stability and change in concentration of crime at micro-places, including the extent to which the same places consistently rank among those with the highest crime counts over time within a city. As described above, Levin et al. (2017) report that a small proportion of micro-places in St. Louis accounted

for a relatively large proportion of crimes each year from 2000 to 2014, with 5% of street segments accounting for on average 54.7% of violent crime and 37.1% of property crime annually. There is little year-to-year variability in the concentration of violent crime (Min = 51.8%, Max = 61.3%, SD = 2.6%) and property crime (Min = 38.2%, Max 41.6%, SD = 1.0%) among segments across study years. Moreover, approximately 76% of segments never appear in the top 5% of segments for violent crime and approximately 73% of segments never appear in the top 5% of segments for property crime, revealing considerable within-segment stability over time. Yet among the remainder of segments that *were* in the top 5% at least one year during the 15 year study, there is considerable year-to-year change. For example, 4.1% of street segments ranked in the top 5% of segments for violent crime for more than 5 years of the 15 year period; only 0.01% of segments were consistently in the top 5% for the entire study period. In short, while the percentage of crimes concentration was relatively stable, the composition of segments contributing to that concentration changed from year to year.

Distribution of Crime at Micro-Places: Street-to-Street Variability, Clustering, or Both?

In addition to examining the concentration of crime at micro-places within cities and the degree of stability and change over time at micro-places, crime and place scholars have also begun to examine the spatial relationships among street segments. For example, do high crime micro-places tend to cluster within cities? Groff et al. (2010) suggest that if street segments of similar temporal crime trajectories cluster spatially, there is little need for micro-level place investigation or intervention. Conversely, street-to-street variability in crime trajectories would highlight the need for targeted interventions at small scale units. They analyze the developmental trajectories produced by Weisburd et al. (2009) using crime incident data from Seattle from 1989 to 2004 to explore the spatial pattern of street segments and determine whether certain trajectories are collocated spatially or if they are spatially independent (see also Weisburd et al. 2012). Their analyses reveal evidence of both clustering and street-to-street variability. In particular, clustering was most pronounced among chronically high crime street segments, but many street segments had temporal trajectory patterns that were unrelated to their adjacent street segment neighbors. They found no evidence of repulsion (i.e., temporal trajectory patterns at further distance than expected by chance). Moreover, they observed considerable geographic dispersion of crime free and low stable segments throughout the city, indicating such micro-places can be found in all types of neighborhoods.

In their study on Albany's spatial patterns of crime trajectories at street segments from 2000 to 2013, Wheeler et al. (2016) find that high crime segments were more clustered than expected by chance, and that high crime segments and low crime segments were further from one another than expected by chance. Wheeler and colleagues note that there was still considerable street-to-street variability in Albany, and the more pronounced clustering observed in Albany may indicate larger neighborhood level processes that contribute to crime risk.

In a study analyzing over 2 million geocoded emergency and non-emergency requests to Boston's 911 and 311 systems in 2011 to 2013, O'Brien and Winship (2017) examine the distribution of violent crime, physical disorder, and social disorder across addresses, street segments, and census tracts. Findings show evidence of year-to-year stability in crime and

disorder at the address-level, though they did observe some year-to-year changes, which the authors interpret as potential "flare-ups" in a given year. Moreover, they report that streets and census tracts displayed greater year-to-year persistence than addresses, perhaps revealing diffusion of events from one neighbor to others nearby (O'Brien and Winship 2017). More recently, O'Brien et al. (2022) used these data to identify acts of public violence in Boston neighborhoods. While they report that violence concentrates within all neighborhoods, there is substantial variation in the *degree* of concentration. That is, a few high crime hot spots generated nearly all the violence in some neighborhoods, while a greater number of more moderate crime hot spots generated most of the violence in other neighborhoods.

In sum, the reviewed research findings have focused on the 1) concentration of crime at micro-places within cities, 2) the degree of stability and change over time at micro-places, and 3) the spatial relationships among micro-places within cities. The first of these has primarily been explored by reporting the relatively large percentage of crimes that occur at a relatively small percentage of micro-places. Yet, as many have noted (e.g., Chalfin et al. 2021), this is not necessarily evidence of non-random clustering, and therefore many studies include significance tests to confirm that the observed concentrations differ significantly from clustering expected by chance (e.g., Sherman et al. 1989; Weisburd et al. 2009). The second of these (i.e., stability and change at micro-places) has been explored in two ways: by examining street segment developmental trends (i.e., trajectories) and consistency in membership in the top 5% of crime segments within a city (e.g., Levin et al. 2017). The third of these (i.e., the spatial relationships among high and low crime micro-places) has largely been examined by testing whether similar crime trajectories collocate spatially within cities. Below we describe how we build on and extend this growing literature by exploring additional dimensions of spatiotemporal crime patterns within and across six large U.S. cities.

The Present Study

In this study, we investigate additional aspects of spatiotemporal crime patterns by using alternative methods to analyze crime incident data from six large U.S. cities from 2008 to 2018 to examine stability and change in crime at micro-places. Specifically, we examine the following: (1) the degree of crime concentration at micro-places across a diverse set of cities; (2) the spatial clustering of high and low crime micro-places within cities; (3) the presence of outliers within those clusters; and (4) the extent to which there is stability and change in micro-place classification over time. The approach we use identifies statistically significant high and low crime street segment clusters and outliers, which provides information about a segment's crime in a given year relative to its global and local neighbors. We describe the method more fully below, but it essentially detects clusters of street segments that have more or less crime than would be expected by chance given citywide crime levels. It also identifies segments within clusters that are significantly different from their local spatial neighbors (e.g., a safe street in a dangerous area). We then track stability and change in each segment's classification (based on global crime levels and local spatial neighbors) over the course of the study period. In light of the notion of "flare-ups" reported by Levin et al. (2017) and the trajectory declines in crime that mirrored city-wide declines noted in some studies (e.g., Curman et al. 2015; Wheeler et al. 2016), using within-year comparisons to define clusters and outliers identifies crime problem areas (and safe areas)

in contemporaneous terms relative to city-wide crime levels and local spatial neighbors, even as year-to-year absolute crime levels change. This approach is informed by research findings reviewed above about micro-place crime concentration, stability, change, and spatial collocation, while offering specific location information about a street segment's crime level in relation to its neighbors and allowing for cross-city comparisons.

Study Cities and Data Sources

The research uses data from six of the largest cities in the United States – Chicago, Los Angeles, New York City, Philadelphia, San Antonio, and Seattle. As described in Table 1, these cities vary in terms of urban structure, location, sociodemographic characteristics, and economics. Incorporating six cities in the analyses allows for cross-city comparisons in spatiotemporal crime patterns across diverse locations. For example, although Seattle is the smallest city in terms of population in the study, it has the highest educational attainment, median home value, and median gross rent compared to the other cities. Conversely, Philadelphia has the highest poverty rate and lowest income levels among the study cities. Finally, although San Antonio is one of the most populated cities in the U.S. and the only city in the study with a population gain over the last year, it is also the least dense city in the study. See Table 1 for a more detailed comparison of the six cities.

This study uses crime incident data gathered from the six U.S. municipal police departments. Each municipality provided reported crimes from 2008 to 2018, with the exception of San Antonio, which is restricted to 2008 to 2016.[2] The street segment is the unit of analysis in this study. The xy coordinates were provided for each crime incident, which offers the most precise location the crime occurred and allows for any aggregation method. The crime incident coordinate data were added as an xy event layer and converted to a shapefile. The street shapefiles were gathered from each city's geographic information system (GIS) portal and processed by using the feature to line command to create a segment at every intersection. Each segment was assigned a unique identification number. A spatial join between the crime incidents and the nearest street segment was conducted to calculate the total crime count assigned to each street segment.[3]

Analytic Technique

Local Moran's I, also referred to as Cluster and Outlier Analysis and used as a local indicator of spatial association (LISA), was used to identify statistically significant high crime and low crime clusters and spatial outliers within each city for each year of the study (Anselin 1995). This is one of the primary exploratory analytical strategies used in a range of disciplines to classify spatial clusters and spatial outliers. This method provides a statistic for each location (street segment), establishes a proportional relationship between the

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[2] The City of San Antonio was unable to provide the crime incident data for 2017 and 2018 because data sharing is under review with the Texas Office of the Attorney General.

[3] Crime incidents that occurred at intersections were assigned to the nearest street segment. Since this study analyzes total crime incidents and is interested in overall spatial distribution patterns of these incidents, the characteristics of crime incidents that occur at intersections are not different from those at street segments so there is no need to drop or analyze these crime events separately.

Table 1 Six Cities comparison

	Chicago	Los Angeles	New York	Philadelphia	San Antonio	Seattle
Location by U.S. region	Mid-West	West	Northeast	Northeast	Southwest	Northwest
Population	2,696,555	3,849,297	8,467,513	1,576,251	1,451,853	733,919
Population % change from previous year	− 1.8%	− 1.1%	− 3.8%	− 1.7%	1.2%	− 0.2%
Population density (sq. mi.)	11,841.8	8,092.3	27,012.4	11,379.5	2,879.8	7,250.9
Total land area (sq. mi.)	227.63	468.67	302.64	134.10	460.93	83.94
Non-white	41.6%	28.5%	44.2%	53.4%	11.8%	31.8%
Hispanic	28.6%	48.1%	28.9%	15.1%	64.7%	7.1%
Foreign born	20.3%	36.3%	36.4%	14.3%	14.0%	19.4%
Owner-occupied housing units	45.3%	37.0%	32.8%	52.8%	53.8%	44.9%
Median value of owner-occupied units	$267,000	$670,700	$635,200	$171,600	$156,700	$713,600
Median gross rent	$1,154	$1,523	$1,489	$1,084	$1,025	$1,702
Population 25 + years with bachelor's degree	41.1%	35.6%	39.1%	31.2%	26.4%	65.0%
Median household income	$62,097	$65,290	$67,046	$49,127	$53,420	$97,185
Persons in poverty	17.3%	16.9%	17.3%	23.1%	17.6%	10.2%

U.S. Census Bureau QuickFacts by city 2020–2021 and 2016–2020 ACS 5-year estimates

local statistics (group of neighboring street segments) with the global statistic (city) (Anselin 1995), and produces classifications that can be used for cross-city comparisons. As a local spatial metric, Cluster and Outlier Analysis clearly visualizes high (or low) crime clusters and street-to-street variability of statistically significant high (or low) crime street segments in low (or high) crime areas. Clusters are areas where a street segment and its neighbors are similar and have more (or less) crime than would be expected in a random spatial distribution. An outlier is a street segment that is dissimilar from its neighbors and falls within a statistically significant high or low crime cluster. It is important to note that the high/low classifications are relative to the local neighbors and global statistic of each city and should not be interpreted in absolute terms.

The formula for Local Moran's I produces a Moran's I value that is a relative measure that can only be interpreted by z-scores and pseudo p-values to determine statistical significance. A positive Moran's I indicates a street segment's neighbors are similar in low or high crime counts and a negative value signals the neighbors are dissimilar, referred to as outliers, in low or high crime counts. The Local Moran's I statistic is expressed as (Anselin 1995):

$$I_i = \frac{z_i - \bar{z}}{\sigma^2} \sum_{j=1,j\neq1}^{n} \left[w_{ij} \left(z_j - \bar{z} \right) \right]$$

where I_i is the Moran's I coefficient; z_i is the crime count for each street segment i; $\bar{z}$ is the average crime count of z with the sample number of n in each city; z_j is the crime count z at all other street segments (where $j \neq i$); σ^2 is the variance of the crime count z; and w_{ij} is a weight that captures a quarter mile of neighbors and is calculated as $\frac{1}{d_{ij}}$, the inverse of the distance d_{ij} among street segments i and j. Inverse distance weight (IDW) is applied as the conceptualization of spatial relationship method to give greater weight to adjacent neighbors than those at the boundary consistent with Tobler's (1970) first law of geography—*everything is related to everything else, but near things are more related than distant things* (p. 236).

To identify neighbors, each street segment becomes the center of its own neighborhood and neighbors are recognized in relation to that segment. This is similar to Hipp and Boessen's (2013) idea of egohoods, where neighborhoods are not treated as discrete entities but rather have overlapping boundaries as "waves washing across the surface of the city" (p.289). Drawing on the urban planning field since the unit of analysis represents the urban form, and consistent with Neighborhood Unit theory, New Urbanism, and Transit Oriented Development, spatial neighbors are defined as all street segments within a ¼ mile radius (e.g., Perry 1929; Calthorpe 1993; Nelessen 1994).

There were only a few street segments, less than 0.05% of our sample, with no neighbors using the fixed ¼ mile conceptualization method. The segments with no neighbors do not receive a Moran's I value. Although the Moran's I index cannot be calculated for segments with no neighbors, their crime counts are still used in the global calculation which means the Moran's I index calculation for the rest of the street segments is not hindered by segments with no neighbors. Seattle had the fewest number of street segments with no neighbors (three street segments) using the ¼ mile threshold and San Antonio had the most street segments with no neighbors (83 street segments).

The Local Moran's I index was produced using false discovery rate (FDR) correction and 999 permutations for every street segment for each year known as a conditional permutation (Anselin 1995). This parameter was used since crime counts are skewed and do not

follow a normal distribution. When the crime count at a street segment i is being assessed using Local Moran's I with conditional permutation, the crime count of i is fixed and all the other street segments' crime counts are randomly sampled. That is, the street segment i is not used in the permutation. This is repeated to create a reference distribution. The permutations generate random spatial distribution values to compare to the Local Moran's I values in the original data to uncover the range of Local Moran's I values that could realistically be random. This is known as pseudo significance which is calculated as $\frac{M+1}{R+1}$ whereas R is the number of permutations and M is the number of occurrences where the computed statistic from the permutations is equal to or greater than the observed value (positive Moran's I) or less than or equal to the observed value (negative Moran's I) (Anselin 1995; Zhang et al. 2008). The precision of 999 permutations is a pseudo p-value of $(0+1)/(999+1)=0.001$ (Zhang et al. 2008). For spatial patterns that are statistically significant, the generated Local Moran's I values from the permutations will show less clustering than the actual Local Moran's I values.

This entire process was repeated for every year and every city in the study. A local Moran's I value for each street segment is assigned one of six category types for each year. The categories that are produced by the Local Moran's I method are: (1) Statistically significant low crime segment in low crime cluster (LL); (2) Statistically significant high crime segment in low crime cluster (HL); (3) Statistically significant high crime segment in high crime cluster (HH); (4) Statistically significant low crime segment in high crime cluster (LH); (5) Non-significant segment; or (6) Segment with no neighbors. The purpose of this local statistic is to identify both statistically significant spatial clustering and significant spatial outliers. As an example, a street segment classified as LL is located in an area in the city where crime incidents are low (either no crime or very few crime incidents) relative to the rest of the city and the street segment also has low crime (no crime or only a few crime incidents) similar to its local spatial neighbors. A street segment classified as HL is also located in an area in the city where crime incidents are low (either no crime or very few crime incidents). However, the street segment has more crime incidents than its surrounding neighbors in a given year.

As shown in Table 2, street segments for each location are then summarized based on how they were categorized over the course of the study period. The stable, sporadic, and changing segments and clusters categorization was produced as a descriptive and visual summary of the results from the Local Moran's I analyses to aid in the interpretation of the comparative analyses for the six cities over time. Stable street segments are those that fell in same category for the entire study period. Sporadic street segments are those that were both non-significant and fell into a single significant category during the study period. For example, a LL segment may be classified in one or multiple years in the non-significant category because the segment either experienced a slight increase in crime at one or multiple time points during the study period and/or the number of crime incidents of neighboring segments experienced a slight increase in crime. Overall, the segment has relatively low crime in a low crime area but there may be some years where there was a slight variation in crime on that segment and/or on neighboring segments. In contrast to sporadic segments that experience some change but retain their dominant classification throughout the study period, changing segments and clusters are segments that fell into multiple significant categories during the study period. These segments experienced considerable change during the study period since they either have large increases or decreases in crime incidents year to year or are located in areas that experience a large increase or decline in crime relative to the city as a whole.

Table 2 Defining street segment stability and change over time

Stable segments	Street segments that fell into the same category for the entire study period
No neighbors	Street segments that could not be categorized because they had no neighbors
Non-significant	Street segments that were non-significant throughout the study
LL	Low crime segment in low crime cluster throughout the study
HL	High crime segment in low crime cluster throughout the study
HH	High crime segment in high crime cluster throughout the study
LH	Low crime segment in high crime cluster throughout the study
Sporadic segments	Segment was both non-significant and fell into a single significant category during the study
LL and NS	Low crime segment in low crime cluster and non-significant during the study
HL and NS	High crime segment in low crime cluster and non-significant during the study
HH and NS	High crime segment in high crime cluster and non-significant during the study
LH and NS	Low crime segment in high crime cluster and non-significant during the study
Changing segments and clusters	Segment fell into multiple significant categories during the study period
Changing segment in low crime cluster	Segment was both LL and HL during the study
Changing segment in high crime cluster	Segment was both HH and LH during the study
Changing clusters	Segment was in both a low and high cluster during the study

Table 3 Descriptive statistics

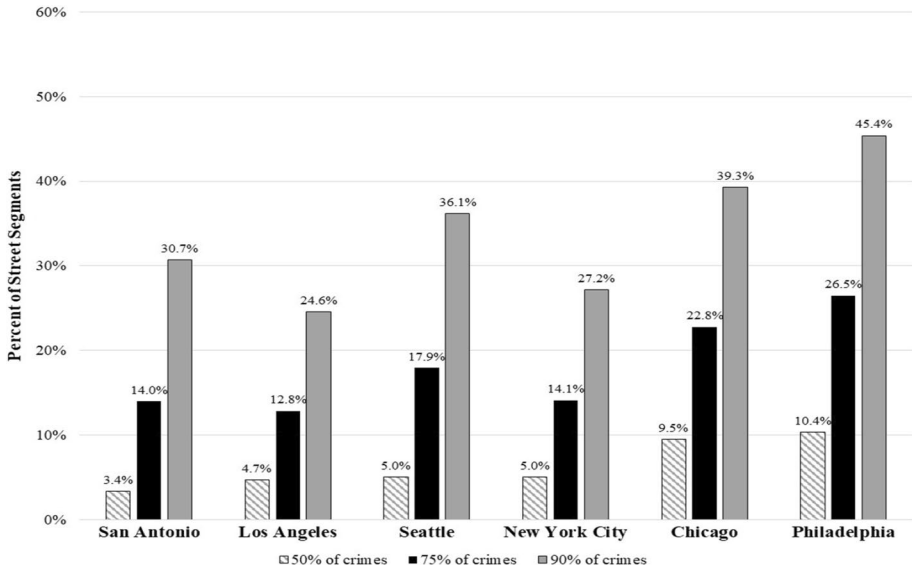| City	No. of street segments	Mean no. neighbors per segment	Mean no. of crimes per segment-year
Seattle	25,284	73.6	1.7
Philadelphia	42,468	101.9	4.2
Chicago	56,610	60.1	5.6
San Antonio	67,312	48.3	2.3
Los Angeles	107,898	70.2	2.0
New York City	123,890	104.7	3.9

Fig. 1 Distribution of Crimes Across Street Segments within Cities

Results

The number of street segments per city varies from 25,284 segments in Seattle to 123,890 in New York City (refer to Table 3).[4] San Antonio street segments have the least amount of neighboring street segments within a quarter mile with a mean of approximately 48 neighbors per segment, while New York City has the most with a mean of roughly 105 neighbors per segment. The mean number of crimes per segment each year also varies by city. Chicago and Philadelphia have the highest mean number of crimes on each street segment per year (5.61 and 4.22, respectively), while Seattle and Los Angeles have the lowest mean number of crimes per year (1.69 and 1.96, respectively).

Figure 1 displays the distribution of crimes across street segments for each city during the study period. In all cities, most crime is concentrated at a small proportion of street segments. In San Antonio, for example, 50% of crimes during the study period occurred at just 3.4% of street segments. Approximately 75% of crimes during the study period occurred at just 14.0% of street segments in San Antonio. Finally, 30.7% of segments experienced 90% of crimes in San Antonio during the study period. San Antonio has the most concentration of crime at the smallest percent of street segments compared

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[4] Several single-city studies that use street segments as the units of analysis in the same cities report fewer street segments. Many of these studies are predictive analyses that use different methodological approaches and remove portions of the street network such as freeways and tunnels where crime is unlikely to occur. The present study is not predictive but rather examines overall spatial distribution patterns of crime. Removing areas of the street network is not necessary in this type of analysis since locations in the street network where crime is infrequent is accurately revealed in the spatial distribution results. Changing the underlying spatial structure would incorrectly assign some crime incidents and change the neighbors identified for each street segment in the Local Moran's I analyses, which could lead to incorrect street segment classification.

to all other cities in the study. However, in Philadelphia where crime is the least concentrated as a percent of street segments compared to the other cities, crime is still concentrated – 50% of crimes during the study period occurred at just 10.4% of street segments, 75% of crimes at 26.5% of street segments, and 90% of crimes at 45.4% of street segments.

This concentration is consistent with extant research that finds crime is not evenly distributed across micro-places and a small portion of street segments account for a majority of all crime (e.g., Braga et al. 2010; Curman et al. 2015; Gill et al. 2017). Yet as Chalfin et al. (2021) note, this is not necessarily evidence of crime concentration, especially when examining relatively rare events. Therefore, we also examined whether the concentration of crime across segments is greater than would be expected by chance. To do so, we tested whether the observed crime distribution across street segments for each city deviates significantly from the simple Poisson model of chance using the one-sample Kolmogorov–Smirnov test (see Sherman et al. 1989). The distribution of crime for each city deviated significantly from the simple Poisson model of chance ($p < 0.001$), indicating higher concentrations were observed than expected by chance.

Expanding on prior micro-place crime concentration research, the spatial patterning of crime across each city is investigated by examining clustering of high (and low) crime street segments each year. Figure 2 highlights three key findings with respect to the non-random spatial clustering of crime across micro-places. The first two key findings reveal consistency across all six cities with respect to the prevalence and stability of high (low) crime clusters. First, low crime street segments in statistically significant low crime clusters are much more prevalent in all cities compared to high crime street segments in statistically significant high crime clusters. Second, within each city, the proportion of street segments that are like their neighbors and fall within a statistically significant high or low crime cluster is relatively stable over time. Third, between cities, there is variation in the distribution of clustering of high (low) crime street segments in high (low) crime clusters. To illustrate, the average proportion of street segments that have high crime and are within a high crime cluster is lowest in San Antonio, at approximately 1%, and Los Angeles, just over 2%, and highest in New York City and Chicago, at approximately 9%. For street segments that have low crime and are within a low crime cluster, again San Antonio and Los Angeles have the lowest proportion at approximately 21% and 23% respectively, whereas New York City has the largest proportion at approximately 47%. Although San Antonio has the most concentration at the smallest percent of street segments as shown in Fig. 1, accounting for the spatial distribution of this concentration reveals that those segments do not cluster together to the same extent as in other cities. We return to this finding in the Discussion.

Figure 3 displays the prevalence of street segments that differ significantly from their local spatial neighbors such as a high (low) crime street segment in a low (high) crime cluster. Upon initial visual inspection, coding errors, although a possibility for some outlier occurrences, do not appear to account for this phenomenon. These segments reveal statistically significant street-to-street variability in crime across all cities. With the exception of Seattle, low crime segments in high crime clusters are more prevalent than high crime segments in low crime clusters across the cities. Within each city, like the clusters, the proportion of outliers is relatively stable over time. However, unlike the clusters, there is much less variation between cities although San Antonio, the least dense of the cities, continues to deviate in comparison to the others. San Antonio has the smallest proportion of both types of outliers at approximately 1%, while the proportion of outliers in all other cities range from 2 to 5%.
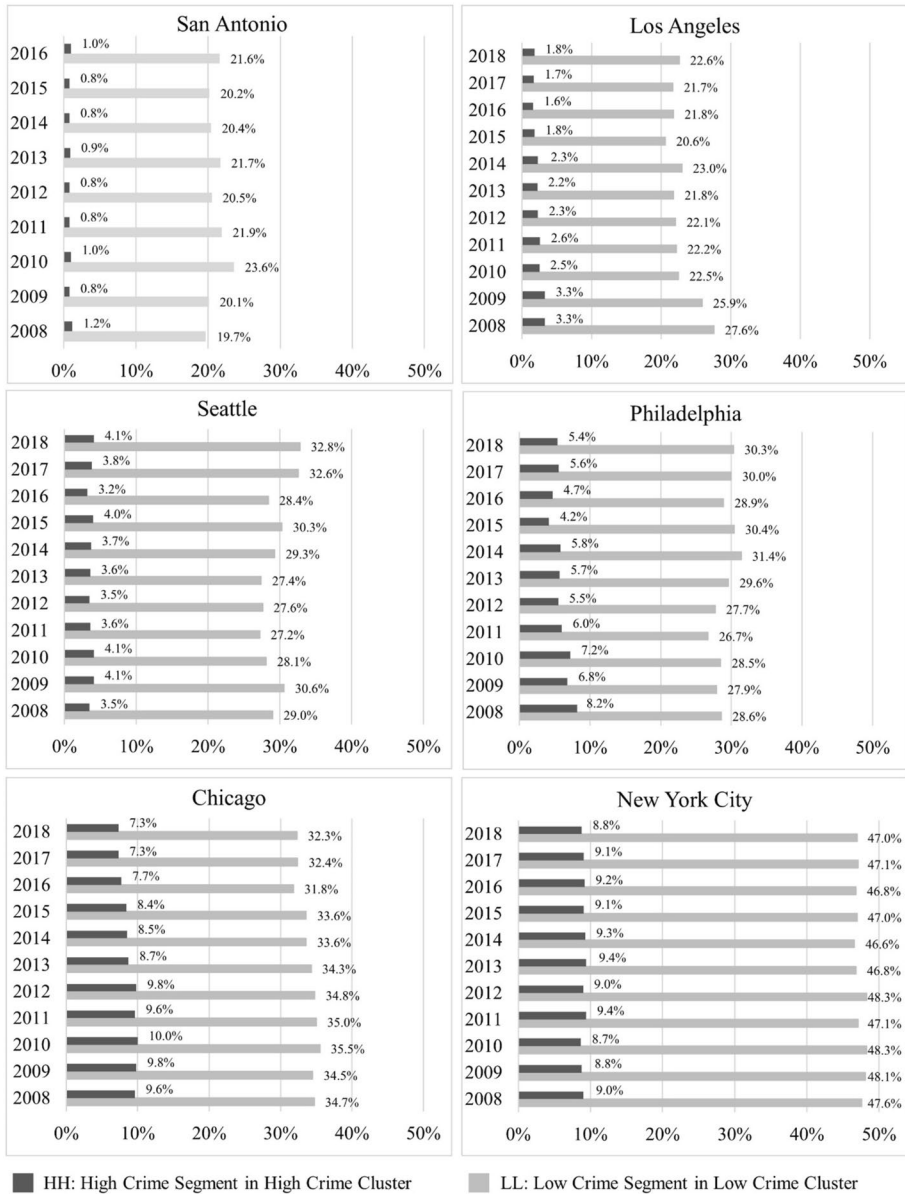
Fig. 2 Year-to-Year Statistically Significant Street Segment Clusters

The first part of the analyses above identified street segment level crime concentration, clustering, and outliers over time for each city, but does not address the extent to which individual street segments remain stable or change over time. Table 4 summarizes the proportion of street segments that remained stable (fell in the same category for the entire study period), were sporadic (street segments that were both non-significant and fell into a single significant category during the study period), and changing segments and clusters
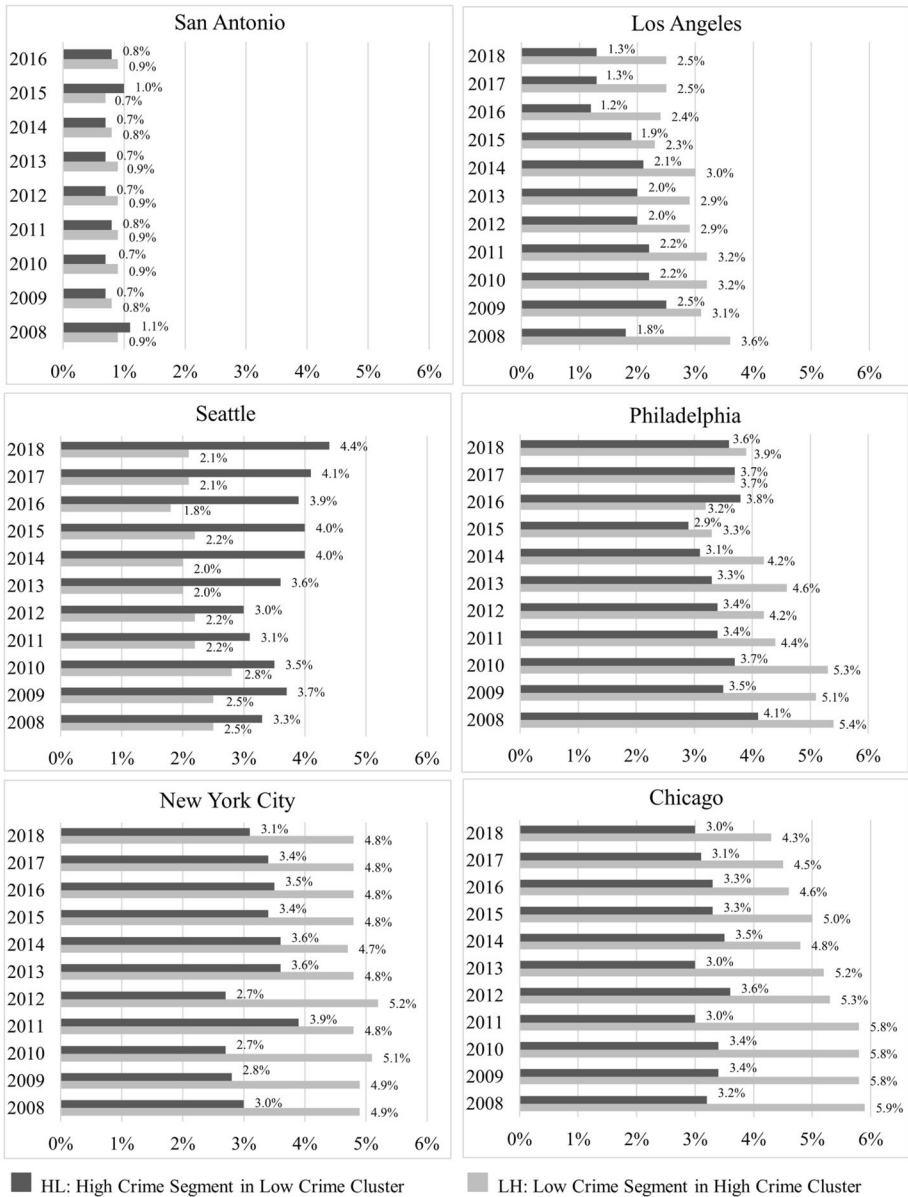
Fig. 3 Year-to-Year Statistically Significant Street Segment Outliers

that fell into multiple significant categories during the study period. Street segments displayed a great deal of stability across all cities. A majority of street segments in 5 of the 6 cities (and 47.5% in the 6th city) fell in the same category for every year of the study. Sporadic street segments, moving from significant to non-significant (or vice versa) but remaining in the same category, were common during the study period for all cities, ranging from 17.7% of street segments in New York City to 32% in Seattle. It was less common

**Table 4** Stability and Change in Street Segment Clusters and Outliers

	Seattle		Philadelphia		Chicago		LA		NYC		San Antonio	
	N	%	N	%	N	%	N	%	N	%	N	%
Stable street segments	12,022	47.5	22,528	53.0	33,360	58.9	65,673	60.9	82,343	66.5	46,615	69.3
No neighbors	3	0.0	17	0.0	10	0.0	51	0.0	14	0.0	83	0.1
Non-significant throughout the study	9,227	36.5	15,262	35.9	18,125	32.0	52,625	48.8	30,146	24.3	40,326	59.9
LL throughout the study	2,250	8.9	6,297	14.8	12,287	21.7	11,927	11.1	42,969	34.7	6,086	9.0
HL throughout the study	6	0.0	114	0.3	146	0.3	43	0.0	354	0.3	6	0.0
HH throughout the study	386	1.5	599	1.4	2,101	3.7	534	0.5	6,501	5.2	87	0.1
LH throughout the study	150	0.6	239	0.6	691	1.2	493	0.5	2,359	1.9	27	0.0
Sporadic street segments	8,085	32.0	12,182	28.7	14,354	25.4	31,028	28.8	21,908	17.7	17,540	26.1
LL and NS	6,507	25.7	7,018	16.5	7,936	14.0	22,714	21.1	14,249	11.5	15,026	22.3
HL and NS	435	1.7	680	1.6	843	1.5	1,674	1.6	1,132	0.9	572	0.8
HH and NS	640	2.5	2,486	5.9	3,201	5.7	2,530	2.3	3,174	2.6	839	1.2
LH and NS	503	2.0	1,998	4.7	2,374	4.2	4,110	3.8	3,353	2.7	1,103	1.6
Changing segments and clusters	5,177	20.5	7,758	18.3	8,896	15.7	11,197	10.4	19,639	15.9	3,157	4.7
Changing segment in low crime cluster	4,382	17.3	4,800	11.3	5,364	9.5	7,421	6.9	13,091	10.6	2,329	3.5
Changing segment in high crime cluster	794	3.1	2,882	6.8	3,422	6.0	3,584	3.3	6,445	5.2	754	1.1
Changing clusters	1	0.0	76	0.2	110	0.2	192	0.2	103	0.1	74	0.1
Total	25,284	100.0	42,468	100.0	56,610	100.0	107,898	100.0	123,890	100.0	67,312	100.0
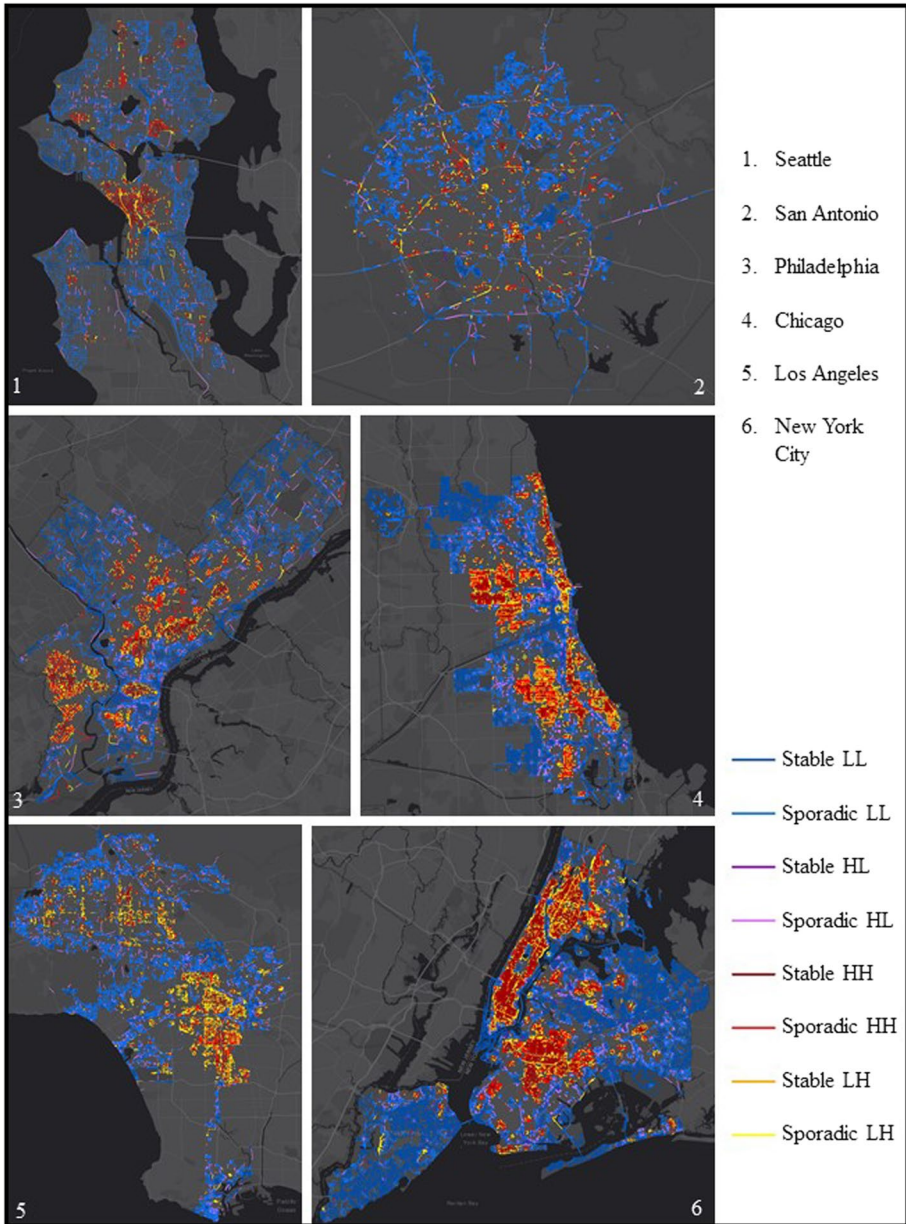
Fig. 4 Stable and Sporadic Street Segments

for street segments in each city to fall into multiple significant categories during the study. The most common form of change that was consistent across all cities was within low crime clusters, ranging from 3.5% of street segments in San Antonio to 17.3% in Seattle. Change within high crime clusters was consistently less common too, ranging from 1.1% of street segments in San Antonio to 6.8% of street segments in Philadelphia. Changing
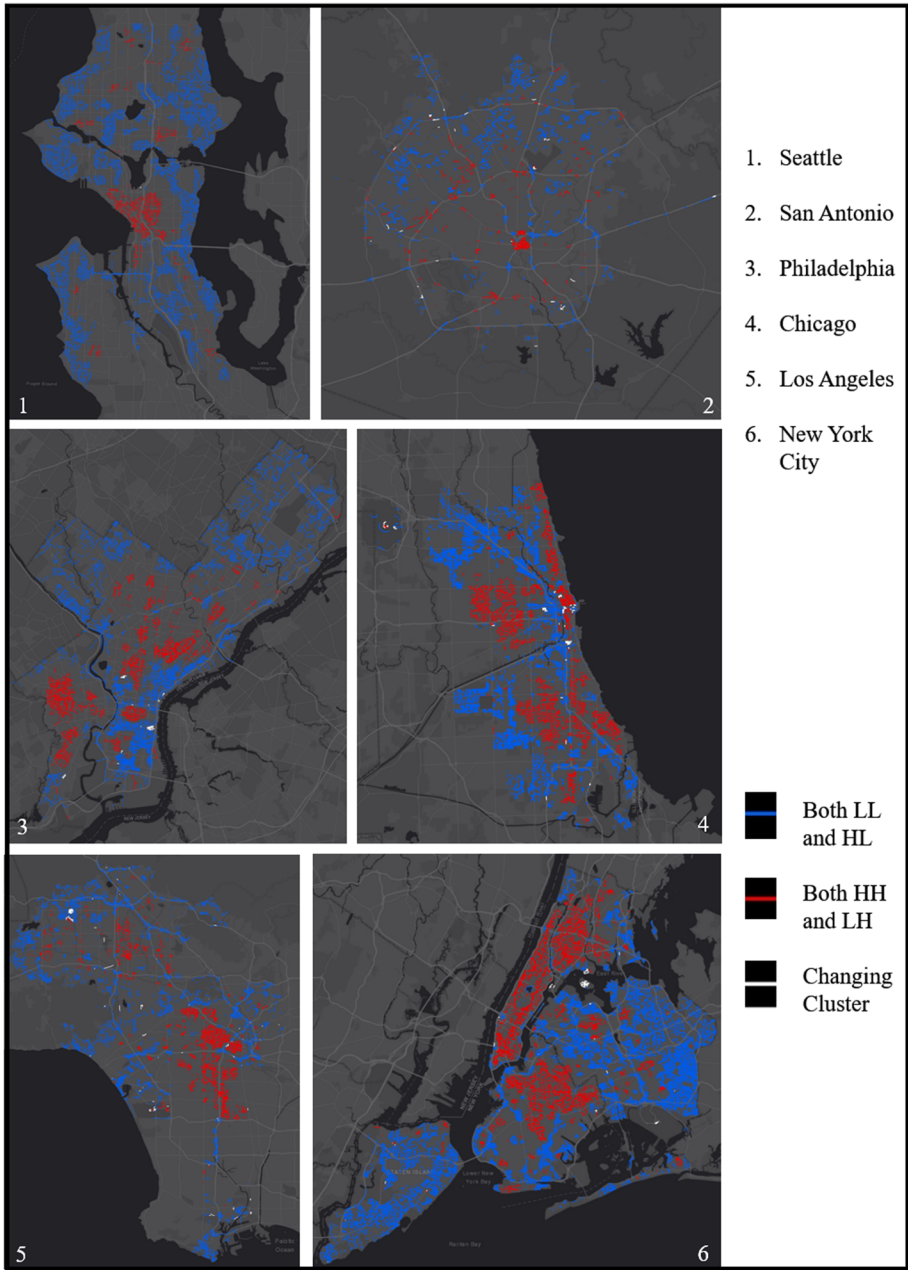
Fig. 5 Changing Segments and Clusters

clusters were rare in all cities, with less than one percent of street segments in any city falling in both a low crime cluster and a high crime cluster over the course of the study. The proportion of street segments falling in a given category varies across cities, but

importantly the rank order of the proportion of segments that are stable, sporadic, or changing is the same across all six cities.

Figure 4 visualizes the spatial distribution of stable and sporadic street segments in each city. This figure provides insight into the location of the stable street segments revealing that HH street segments are generally clustered and located in the densest areas in the core and urban nodes of the city and LL street segments generally expand across the suburbanized areas of the city and along the outer edges of the city limits. The sporadic segments, which are statistically significant in only one category during the study period and are non-significant for at least one point of time, tend to buffer the street segments that consistently fall within one of the stable categories over the entire study period. The spatial distribution also further emphasizes two key findings highlighted above: 1) the majority of the street segments remain stable over time; and 2) there is street-to-street variability in crime classifications (denoted by the colors purple=HL and yellow=LH in the figure).

Figure 5 displays the spatial distribution of changing segments and clusters. This figure underscores that few areas change from low (high) crime to high (low) crime clusters over time (denoted by the color white in the figure). Some street segments in high crime clusters have one or multiple years in which crime drops substantially relative to the average crime in the area (denoted by the color red). Some street segments in low crime clusters have one or multiple years in which crime increases substantially relative to the average crime in the area (denoted by the color blue).

Understanding the extent to which high/low crime clusters and outliers remain stable or how rapid they change over time not only further informs the tactical decisions for prioritizing areas but may also play a role in strategic planning for prevention. The identification of consistent high crime clusters allows for meso-level resource allocation whereas street segment outliers – and especially high crime outliers that are stable over time – call for targeted interventions at small scale units. The identification of outliers raises interesting questions about the tight coupling of crime and place such as how a low crime street segment can insulate itself from nearby criminal activity over time, or conversely, why a high crime street segment may persist in a relatively safe neighborhood. We revisit the relevance of these relatively rare but potentially informative places in the Discussion.

Discussion

Expanding on prior crime and place research, this study underscores the importance of investigating the spatial patterning of crime concentration at small scales and highlights additional aspects of spatiotemporal crime patterns that can inform theory and practice. The data and methods employed allowed us to contribute to the literature on crime and place in three important ways. First, we used data from six large U.S. cities over an 11-year period, permitting cross-city comparisons that have been limited in the extant research due to the predominance of single-city studies that often examine different time periods using varying methods. Second, we used cluster and outlier analysis that detects clusters of street segments that have more or less crime than would be expected by chance given citywide crime levels, as well as segments within clusters that are significantly different from their local spatial neighbors. This method highlights both the clustering and street-to-street variability of crime at micro-places in any given year within the study cities. Street-to-street variability emphasizes the important role of methodological strategies at the micro-scale and use of local statistics to uncover heterogeneity in areas that have traditionally be treated

as homogenous units like neighborhoods. Third, we then tracked stability and change in each segment's classification (based on global crime levels and local spatial neighbors) over the course of the study period. Categorizing segments relative to contemporaneous crime levels of their local and global spatial neighbors highlights an additional aspect of crime patterning that acknowledges broader macro-level trends that may impact a segment's absolute level of crime independent of that segment's relative priority as a city's safety concern.

Consistent with the extant research on the spatial distribution of crime across microplaces within cities and Weisburd's (2015) *law of crime concentration*, crime was significantly concentrated at relatively few street segments in Chicago, Los Angeles, New York City, Philadelphia, San Antonio, and Seattle, though the degree of concentration varied across cities. Specifically, 50% of crimes during the study period were located at just 3.4% of street segments in San Antonio compared to 4.7% in Los Angeles, 5.0% in Seattle and New York City, 9.5% in Chicago, and 10.4% of segments in Philadelphia. Though explaining the source(s) of these cross-city differences goes beyond the scope of our univariate analyses, it is interesting to note the role the urban form and spatial order of each city may play. For example, concentration may be loosely and inversely related to population density (with New York City as an exception).

Yet when we examined the degree to which high crime segments were clustered, a different picture emerged. The City of San Antonio, which has the most concentration at the smallest percent of street segments, displayed the *least* amount of clustering compared to the other five cities, thus highlighting the value of analyzing both the distribution of crime at a global scale and the spatial patterning of crime concentration at the micro-level. On a practical level, the perceptions of safety and lived experiences of residents, visitors, employees, patrons, and business owners related to a specific micro-place (in this case, a street segment) are likely informed not just by crime on that segment, but also by the surrounding street segments. In addition, the effect is likely not invariant depending on the segment's position relative to its neighbors. In other words, living or working on a high crime segment embedded amongst dozens of high crime segments is likely a very different experience than living or working on a high crime segment where real and perceived safety is a block or two away.

In addition to the observed clustering, the findings also reveal statistically significant street-to-street variability in the form of high and low crime outliers, or street segments that differ significantly from their local spatial neighbors. These distinctions convey additional knowledge for crime and place research to inform the allocation of resources. The identification of clusters, specifically high crime clusters in this case, identify areas within a city for resource allocation. However, it is the street-to-street variability in these high crime clusters, both high crime street segments (HH) and low crime street segments (LH), that informs targeted micro-place intervention.

Moreover, the temporal component assessed in this study offers ancillary evidence for spatial prioritization and resource allocation in a given year. As Levin et al. (2017) suggest from using global neighbors' contemporaneous crime levels to identify high crime places and distinguishing them from places that are highly concentrated intermittently, contrasting enforcement strategies are necessary for reducing crime. In analyzing temporal crime patterns, we learn that although there is considerable stability in crime at the street segment level across all cities, each city revealed a proportion of street segments where crime levels were changing relative to local and global spatial neighbors, which signals divergent policy responses. High crime street segments in high crime clusters that remain persistent over time can have a sizable impact on citywide crime rates (Weisburd et al. 2004). The

persistence of this trend may be driven by systemic root causes that call for resource allocation beyond policing interventions. Conversely, a very specific event (e.g., opening/closing of a business, change in land use, property being vacated) may be the driver of a sporadic or changing street segment, especially one that differs from its spatial neighbors. This event may only require attention at one point in time and not necessarily a specific intervention or permanent resources.

From a theoretical perspective, our findings raise questions about the underlying causes of spatiotemporal crime patterns. As we noted above, existing criminological theory and research suggest the mechanisms that produce spatial patterning can operate across different spatial scales, with *both* micro-place features *and* meso-level characteristics contributing to crime risk (e.g., Wilcox and Tillyer 2018; Jones and Pridemore 2019; Tillyer et al. 2021; O'Brien et al. 2022). Our findings, which reveal both street-to-street variability and the clustering of high crime places, are not inconsistent with a multilevel understanding of spatiotemporal crime pattern formation. However, our methodology does not allow us to rule out other explanations, as such findings are open to multiple interpretations. Groff et al. (2010), for example, view the clustering of high crime trajectory segments as reflecting similarities in the social and built environments of nearby micro-places. Conversely, Wheeler et al. (2016) note such clustering may indicate a diffusion process, whereby crime at micro-places are influenced by nearby places, or broader neighborhood-level mechanisms.

Despite the strengths of the current study's methodology, there are some limitations that point to directions for future research. First, although many of the findings from the study were consistent across six diverse municipalities and are generalizable to large American cities, the study cities are among the largest and most studied in the United States. It is unclear if the findings are applicable to other cities and towns in America. Would smaller, less diverse cities with fewer policing resources exhibit similar patterns? Future research should examine spatiotemporal patterning in municipalities that share some of these other characteristics to determine if the results are generalizable to a broader set of American cities.

Second, future research is imperative to uncover the dynamics of street-to-street variability and its potential causes. Specifically, the identification of outliers raises compelling questions about how some low crime micro-places insulate themselves from their local spatial neighbors (and less common, why some micro-places experience high levels of crime despite their generally safe surroundings). There is an immense amount of knowledge that can be gained about safe havens in dangerous neighborhoods and dangerous streets in safe neighborhoods. It is likely that other factors such as distinct urban features (e.g., density, land use, street network), public and private investment/disinvestment, management practices, guardianship, policing strategies, security features, to name a few, may be potential explanations as to why some streets have crime profiles and trajectories that differ than their neighbors. Furthermore, examining this phenomenon between cities is imperative as San Antonio and Los Angeles, the least dense of the cities, have the lowest proportion of statistically significant clusters and outliers, and subsequently the fewest segments and clusters that changed over time. This indicates factors such as urban features may play a substantial role in geographic and temporal crime patterns.

Third, though beyond the scope of this paper, future work should also examine spatiotemporal patterning – and clusters and outliers, specifically – at the micro-level by crime type. Andresen et al. (2017) examined spatial concentrations and stability of crime type specific trajectories in Vancouver, Canada for assault, burglary, robbery, theft, theft of vehicle, theft from vehicle, other crime, and total. They feature several meaningful distinctions

by disaggregating crime types that further informs resource allocation. To illustrate, it was only through the disaggregation of crime types when the change in crime trajectories were identified in some locations, and in several micro-places a specific type of crime was driving crime rate trends. This precise information informs the type of resources and interventions that will be the most effective, and may distinguish some cluster types from others within cities.

The present study's methodology is a valuable contribution to the crime and place literature that offers several important revelations about spatiotemporal crime patterns worth emphasizing. First, the degree of *clustering* of high crime street segments (i.e., the spatial relationship among high crime street segments), in addition to the *distribution* of crime across street segments (i.e., "the law of crime concentration"), is an important dimension of a city's crime landscape. For example, our analyses revealed San Antonio displayed the least amount of *clustering* but the highest degree of *concentration*. As noted above, this undoubtedly has important implications for perceptions of crime and our responses to it. Second, this methodology uses within-year comparisons to define clusters and outliers in contemporaneous terms relative to city-wide crime levels and local spatial neighbors, thus identifying potential public safety area priorities, even as year-to-year absolute crime levels change. This provides different information than prior studies that relied on trajectory analyses to categorize segments. Related, by tracking each segment's classification over the study period, this methodology reveals the degree of change among segments (ranging from 4.7% in San Antonio to 20.5% in Seattle). Finally, the identification of outliers should spur further theoretical and empirical attention. Recent research has highlighted how characteristics of nearby places can affect crime at micro-places (e.g., Tillyeret al 2021). While a small percentage of segments in our study remained outliers over the course of the study, it was more common for outlier segments to change over the course of the study, becoming more or less similar to their local spatial neighbors. Understanding the mechanisms that influence such change can inform policy interventions to maximize public safety benefits across an urban landscape. Collectively, these findings demonstrate the added value of the present study's methodology, both supporting existing findings from prior research and providing additional information about spatiotemporal crime patterns.

This study builds on the existing crime and place literature to examine the degree of crime concentration at micro-places across six large cities, the spatial clustering of high and low crime micro-places within cities, the presence of outliers within those clusters, and extent to which there is stability and change in micro-places' classifications over time. The findings revealed some similarities across cities, including considerable stability over time in segment classification. There were also cross-city differences that warrant further investigation, such as the varying levels of spatial clustering. Moreover, micro-place outliers – including ones that are stable over time *and* those that change over time to become more (or less) like their neighbors – offer an opportunity to understand the dynamic mechanisms that shape a city's spatiotemporal crime patterns.

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