Metropolitan local crime clusters: Structural concentration effects and the systemic model

Lallen T. Johnson a,⁎, Ralph B. Taylor b, Elizabeth R. Groff b

a Department of Criminology and Justice Studies, Drexel University, 3141 Chestnut St, Philadelphia, PA 19104
b Department of Criminal Justice, Temple University, 1115 Polet Walk, Gladfelter Hall, 5th Floor, Philadelphia, PA 19122

Abstract

Purpose: Using community structure and the racial-spatial divide as a framework, this study examines whether geographic sub-regions of violent crime exist in a large metropolitan area, and if the systemic model of crime can predict them. In addition, surrounding social structure measures are included to determine whether they demonstrate the same violent crime links seen in recent work on concentration impacts.

Methods: A LISA analysis is used to identify violent crime clusters for 355 jurisdictions in the Philadelphia (PA)-Camden (NJ) primary metropolitan area over a 9-year period. Multinomial logit hierarchical/mixed effects models are used to predict cluster classification using focal and lagged structural covariates.

Results: Models confirmed links of focal jurisdiction socioeconomic status and residential stability with sub-region classification. Models with spatially lagged predictors show powerful impacts of spatially lagged racial composition.

Conclusions: Findings extend work on racial concentration effects and the basic systemic model to metropolitan sub-regions. Implications for shifting spatial inequalities in metropolitan structure and questions about responsible dynamics merit attention.

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Introduction

Documented spatial variation of crime or delinquency levels across ecological units ranging in size from nations to street corners stretches back many decades, and varies by the size of the unit and outcome in question (Baller, Anselin, Messner, Deane, & Hawkins, 2001; Brantingham, Dyreson, & Brantingham, 1976; Groff, Weisburd, & Yang, 2010; Lawton, Taylor, & Luongo, 2005; McCall & Nieuwbeerta, 2007; Messner & Rosenfeld, 2007; Ratcliffe, Taniguchi, Groff, & Wood, 2011). Given all this work, considerable knowledge has accumulated about the connections between crime or delinquency and features of demographic structure across such units (Pratt & Cullen, 2005; Taylor, 2015). But, as Andresen (2011) has pointed out, “investigations into spatial relationships between places” are by comparison far more “limited” (p. 394).

The current work investigates such between-place spatial relationships for jurisdictions in the fifth largest primary metropolitan area in the US. Focusing on local violent crime clusters composed of adjoining jurisdictions, it advances earlier spatial work by exploring the reliability of these local cluster classifications over most of a decade. It extends knowledge about demographic structure and the ecology of crime in two ways: by verifying the relevance of focal jurisdiction demographic elements highlighted in the basic systemic model of crime for neighborhoods (Bursik & Grasmick, 1993), and by examining the roles of spatially lagged racial composition and spatially lagged socioeconomic status to violent crime concentrations (Peterson & Krivo, 2010).

The remainder of the introduction is as follows. Select examples highlighting some of the most relevant between-place work on local violent crime clusters are noted, as are examples of spatially lagged demographic concentration effects on violent crime. Reasons to expect sub-regional violent crime patterning, and expectations about the geography of such patterning, are described. The section closes with a brief statement of key questions.

Between-place work on local violent crime: Select examples at different spatial scales

Violent crime rates exhibit local spatial dependency, with the form of that dependency depending on the crime and the ecological unit in question. County level US homicide rates across four different decades generated local clusters of higher than average counties surrounded by other higher than average counties (Baller et al., 2001). But this relationship appeared only in the southern region of the country, suggesting spatial dependency of county homicide rates depended on positioning within South versus non-South regions.

Using jurisdictions within the Philadelphia (PA)-Camden (NJ) primary metropolitan area, Groff, Taylor, Elesh, McGovern, and Johnson
addressed, however. Con
crime areas?

from the mid-1980s to the mid-1990s. They identi
more susceptible in some years to increasing violent or property crime

First, he found that the demographic links with low-low cluster status
the St. Louis metro area was explicitly exploratory, they did not test the
by-low local cluster; see their Fig. 7.2). Since their analysis of counties in
over time in the location of some clusters (e.g., a high-surrounded-by-
high cluster including St. Louis city in the center of the region) and shifts
over time (e.g., some counties in a low-surrounded-by-low local cluster
along the northern tier of the metro area shifted to a high-surrounded-
by-low local cluster; see their Fig. 7.2). Since their analysis of counties in
the St. Louis metro area was explicitly exploratory, they did not test the
consistency of local cluster classifications across the two periods, nor did
they consider structural covariates of local crime cluster classifications.

Andresen (2011) did address such links in his analysis of 2001 local
crime cluster classifications for dissemination areas, somewhat compara-
table to census block groups in the US, within the city of Vancouver
(British Columbia). For violent crime, he observed high-high local
clusters “in Vancouver’s central business district and Skid Row” where
“commercial land use” was extensive while low-low clusters were
most likely to be found in the “wealthier western portion of Vancouver”
(Andresen, 2011, p. 399). Treating the local crime cluster classification,
including being unclassified, as a nominal outcome, he predicted these
groupings using demographic structural variables capturing socioeco-
nomic status, residential stability, and racial and ethnic composition.1
His results have particular importance for the current investigation.
First, he found that the demographic links with low-low cluster status vs.
unclassified were “generally consistent” with what might be expect-
ed given known violent crime demographic ecological correlates (Pratt &
Cullen, 2005, p. 400). For example, relative low violence was more likely
if unemployment was lower and homeownership was higher
(Andresen, 2011, Table 7). Second, results were less likely to match up
to known community crime demographic correlates for the high-high
clusters, “often ... [proving] opposite the expected sign” (Andresen,
2011, p. 400). Third, both the low-surrounded-by-high local cluster
demographic links, and the high-surrounded-by-low local cluster demographic
links had “more in common with the high-high local crime cluster results”
(Andresen, 2011, p. 400). His findings leave a few concerns un-
addressed, however. Confidence in the utility of local crime clusters
might be enhanced if cluster classifications proved consistent over
time. Further, the failure of Andresen (2011) to observe the expected
demographic correlates for high-high violent crime clusters is troubling.
Would the expected links surface in a test using a different locale with
different sized ecological units? And finally, as Andresen (2011) himself
notes, “Why do immediate spatial neighbors impact the nature of local
crime areas?” (p. 401). He looks to edge effects for an answer, and ear-
lier results with permeability across metro jurisdictions (Groff et al.,
2014) suggest partial applicability of such dynamics. An alternate
frame deserving consideration, however, is concentration effects. For
economically disadvantaged and/or predominantly non-white jurisdic-
tions, being surrounded by structurally similar jurisdictions can intensi-
fy crime-related activities both in surrounding spatial units and in the
focal ecological unit.

Concentration effects

The basic idea of concentration effects is that a community structur-
ally susceptible to high violent crime rates is far worse off if surrounded
by other communities sharing the same demographic susceptibilities.
Such concentration effects come about given the racial-spatial divide and
hypersegregation in US communities (Krivo, Peterson, & Kuhl,
2009; Massey & Fischer, 2000), and tightly linked socioeconomic
inequalities (Peterson & Krivo, 2010).2

Given the racial-spatial divide and linked spatial socioeconomic
differentials, it is no surprise that numerous studies find that being
surrounded by communities which are structurally disadvantaged
links to higher violent crime rates (Mears & Bhati, 2006; Morenoff,
Sampson, & Raudenbush, 2001). Perhaps the most comprehensive
assessment, conducted by Peterson and Krivo (2010), used almost 9,000
census tracts in more than seven dozen US cities. They found that geo-
graphic concentration effects due to spatially lagged racial composition,
after controlling for city and focal neighborhood features, rendered
black vs. white neighborhood violence differentials non-significant
could not produce the same reduction in black vs. white neighborhood
violence differentials. Further, controlling for surrounding violence,
neighborhood racial type, and city features, they found surrounding
levels of residential instability and racial composition significantly
affected violence levels, but surrounding disadvantage levels did not.
Peterson and Krivo’s (2010) results would seem to question some earli-
er works finding significant impacts of surrounding levels of disadvan-
tage on violence.

That question can be reframed into a broader query given the focus
here on local crime clusters. If concentration effects matter not only for
determining the violence level in a focal ecological community but also
for determining membership in a violent crime cluster of local commu-
nities, models with spatially lagged predictors might outperform models
with focal community characteristics in predicting membership
type. Further, if models with spatially lagged structural predictors do
better, which spatially lagged feature provides the best fitting model?
For local violent crime clusters based on positive local spatial autocorre-
lation, Peterson and Krivo’s (2010) research suggests that lagged composi-
tion and lagged residential stability are both relevant, but lagged
SES is not.

Why expect sub-regions of high or low metropolitan violence?

Sub-regions of more or less local violence are expected for many
reasons. Centrally located as well as peripherally located urban jurisdic-
tions along with inner-ring suburban sites have experienced significant
losses in manufacturing jobs over the past four decades, concomitant
with increasingly unequal concentrations of populations of color and of
poverty (Adams, Bartelt, Elesh, & Goldstein, 2008). Suburban jurisdic-
tions nearby some of these locales have experienced withdrawal of cap-
ital even prior to racial and economic shifts (Smith, Caris, & Wyly, 2001).
Other suburban jurisdictions have been or are extremely well off eco-
nomically (Adams et al., 2008). Road and rail transport systems com-
bined with specific locations of large scale land uses like parks, forests
and military bases, and natural barriers like rivers, create differentials
in accessibility across jurisdictions (Groff et al., 2014). Finally, as the
metropolitan area has grown and evolved, populations and jobs have
shifted outward, leaving behind struggling jurisdictions, especially if
those places are small and without a diverse job base.

Most broadly, these metropolitan dynamics would suggest centrally
located high-high local clusters of violent crime and peripherally located
county-level examination of homicides in the St. Louis metro area, and
the patterning that Andresen (2011) observed in the city of Vancouver
itself, along with some theoretical frames (Hawley, 1950) would sug-
gest such a geographic arrangement.

Community structure as an organizing frame

Bursik and Grasmick’s (1993) basic systemic model of crime high-
lights the relevance of three structural precursors of crime- and
delinquency-related social and cultural dynamics: community socio-
economic status, residential stability, and racial/ethnic heterogeneity.
The latter is refocused to racial composition given Peterson and Krivo's (2010) approach to the racial-spatial divide and the links between some of our questions and their approach. These three structural dimensions are well accepted as fundamental features of community structure (Berry, 1965, 1972; Berry & Kasarda, 1977; Golledge & Stimson, 1997; Hunter, 1971). Should all three link to violent crime cluster type in ways aligning with Bursik and Grasmick's (1993) and Peterson and Krivo's (2010) theoretical frames, that might suggest the potential applicability of these models to sub-regional, local violence patterning.

Key questions

In sum, the current work addresses the following key questions. First, do the demographic structural correlates of more violent and less violent crime sub-regions within a large and complex metropolitan area align with expectations based on the basic systemic model of crime (Bursik & Grasmick, 1993) and work on the racial-spatial divide (Peterson & Krivo, 2010)? Unexpected connections observed by Andresen (2011) for high violent crime city sub-regions underscore the openness of this question. Second, work on more or less violent than average sub-regions either has examined only one year (Andresen, 2011) or has noted shifts over time (Messner & Anselin, 2004). This leaves open the question of consistency of violent crime sub-region types across time, and its importance for deepening our understanding of local crime clusters. Third, the most comprehensive work to date on violent crime and concentration effects (Peterson & Krivo, 2010) presents results with conflicting implications about the relative importance of spatially-lagged socioeconomic status versus spatially-lagged racial composition. The current work investigates whether including concentration effects models with spatially lagged predictors generate better fitting models for sub-region classification, and if so, whether lagged socioeconomic status or lagged racial composition proves more important.

Methods

Site

Counties are the basic building blocks of metro areas. The Philadelphia-Camden primary metropolitan area includes four counties in New Jersey (Burlington, Camden, Gloucester and Salem) and five in Pennsylvania (Bucks, Chester, Delaware, Montgomery and Philadelphia). These nine counties contain within them 355 jurisdictions. These are of two types: “municipalities” and “minor civil divisions” and both of these types are “incorporated places.” Minor civil divisions include cities as well as towns, townships, and boroughs serving as “general-purpose local governments” (U.S. Census Bureau, 2013). Municipalities, the second type of incorporated place, include cities in the Philadelphia-Camden metropolitan region (e.g., Philadelphia, Camden, Chester, Coatesville and Salem). The most frequent jurisdiction type in the metro region is the township.

The Philadelphia (PA)-Camden (NJ) primary metropolitan area covers 3,830 square miles. As of 2013, the region’s nine counties had a population of 5,383,081 residents. Its land area is almost four times the size of Rhode Island, and about half the size of Hawaii. Its population is about 3.8 times the size of Hawaii’s and 5.1 times Rhode Island’s. The population on the Pennsylvania side represents 31.8 percent of the entire population in the Commonwealth of Pennsylvania.

Constructing crime rates

Annual counts of murders, rapes, robberies, and aggravated assaults reported by law enforcement agencies across the Philadelphia region were derived from the FBI’s Uniform Crime Report program from 2000 to 2008, and from respective state police reports. Crime counts were divided by population and multiplied by 100,000 to generate violent crime rates per 100,000 population. The average (unweighted) annual municipal crime rate across the Philadelphia region in 2000 was 239.57 per 100,000 residents. Unweighted average violent crime rates were relatively stable until 2006, when they increased to a rate of 256.43. A decrease, however, occurred by 2007 before the region experienced it’s highest average violent crime rate during the study period in 2008 at 266.74.

Outcome variable

The outcome of interest is nominal: membership in a local cluster of relatively high violence, relatively low violence, or mixed violence locales within the broader metro region. Multi-jurisdiction clusters were identified by applying local indicators of spatial autocorrelation (LISA), specifically the Local Moran’s I, to the violent crime rate for each year separately, for the years 2000-2008, to all the jurisdictions (n = 355) in the MSA. The Moran’s I correlation statistic compares each feature’s value on a variable to the group mean of its neighbors on the same variable (Anselin, 1995). This indicates the presence and location of any of the following four statistically significant local geographic patterns: places with high values on a variable adjoining other places also with high values; places with low values on a variable adjoining other places also with low values; places with high values surrounded by adjoining places with low values; and places with low values surrounded by adjoining places with high values. The first two are patterns of positive local spatial autocorrelation; the latter two are patterns of negative local spatial autocorrelation. Each jurisdiction is classified, for each year, into one of the above four categories, or into a category indicating no local cluster membership. The number of jurisdictions in each category, by year, appears in Table 1. The LISA statistics confirmed that jurisdiction-level violent crime rates formed significant local clusters of both types of positive (high surrounded by high, low surrounded by low) and negative spatial autocorrelation (low surrounded by high, high surrounded by low) in each of the study years. All LISAs were computed using Empirical Bayes standardized rates with the standardization using population size.

The two mixed autocorrelation categories (low surrounded by high and high surrounded by low) were later merged into one category of mixed safety (see below). Table 2 provides violent crime descriptive statistics across jurisdiction-years for the three different types of local clusters and the non-clustered jurisdiction-years.

Independent variables

Demographic data were derived from the 2000 decennial census as well as post-censal estimates from GeolYtics for the years of 2001 – 2008.Annual repeated measures of multiple indicators from 2000 to 2008 were constructed for each of the time varying covariates reflecting jurisdiction demographic structure. Table 3 displays descriptive statistics. Indices for socioeconomic status and residential stability were included, with a separate indicator for racial composition. The socioeconomic status index was the average of z-scored median home value, median household income, percent of families above poverty, and the percent of the population that is at least 25 years old with a college education (Cronbach’s alpha = .86 – .88 depending on the year). The residential stability index was the average of z-scored percent owner-occupied housing units, percent non-vacant housing units, percent-married couple households, and percent multi-person households (Cronbach’s alpha = .84 – .88 depending on the year). Racial composition was captured with the proportion of non-Hispanic, white residents. To capture spatially lagged demographic impacts, Empirical Bayes weighted spatially lagged predictors were created using first-order queen contiguity. Adding a year variable (0, 1, 2, and so on) controlled for long-term linear trends. Area was measured as each jurisdiction’s total square mileage to control for variation in
Conditional on the municipality-level random effects. Models were fitted using GLLAMM (Generalized Linear Latent and Mixed Models).8 Multinomial models are preferable to a series of logit estimates because they simultaneously model multiple alternatives, relative to a predetermined base category. This arrangement parallels the contrasts examined by Andresen (2011) and facilitates comparing the current findings with his. The multinomial logit model simultaneously examines three binary contrasts:

- Contrast 1: High crime rate jurisdictions surrounded by other high crime rate jurisdictions (high–high) vs. non-clustered jurisdictions;
- Contrast 2: Low crime rate jurisdictions surrounded by other low rate jurisdictions (low–low) vs. non-clustered jurisdictions; and
- Contrast 3: Mixed jurisdictions (high surrounded by low and low surrounded by high) vs. non-clustered jurisdictions.

As shown in Table 1, 2,514 jurisdiction-years (79%) were not categorized into a local cluster. Three hundred seventy one jurisdiction-years (12%) were positioned in a sub-region of local relative safety, jurisdictions with low violent crime rates, surrounded by others with low violent crime rates. One hundred ninety six jurisdiction-years (6%) were located in sub-regions of local danger, being high violent crime jurisdictions.

Clusters of high–low (n = 80) jurisdiction-years appeared relatively infrequently (1% and 3%, respectively). These clusters represent sub-regions of significantly mixed levels of violence. Given that commonality, and lacking any theoretical specification in community criminology about focal/surrounding differences within such sub-regions, these two patterns of negative spatial autocorrelation were collapsed in the analyses to represent sub-regions of mixed levels of violence. This collapsing also seems justifiable given Andresen’s (2011) finding that the structural correlates of both these mixed types in Vancouver looked similar to the correlates of high-high local crime clusters.

### Expectations of covariate patterning

Given earlier findings based on the basic systemic model of crime and on the racial- spatial divide, we expect the following:

1. high-high cluster membership is more likely to be associated with lower SES, lower residential stability, and lower percentage white population, whether the predictors are focal or lagged, compared to non-clustered jurisdiction years
2. low-low cluster membership, for both focal and lagged predictors, is more likely to be associated with higher SES, higher residential stability, and higher percentage white population, compared to non-clustered jurisdiction years
3. given Andresen’s (2011) findings for mixed local clusters, we expect their covariates to be similar to those for high-high clusters when contrasted with non-clustered jurisdiction years.

### Results

#### Confirming significant outcome variation at the jurisdiction level

An unconditional or null multilevel multinomial model (BIC = 3388.065) indicated, on average across all the years considered, significant variation across jurisdictions in the odds, relative to non-clustered status, of being categorized into a high-high vs. a low-low vs. a mixed local cluster based on violent crime rates (jurisdiction variance = 5.60; SE of variance = .38). Given these results, we continue with multilevel modeling.

### Table 1

<table>
<thead>
<tr>
<th>Outcome cluster</th>
<th>Non-significant</th>
<th>High - Low</th>
<th>Low - High</th>
<th>Non-clustered</th>
<th>Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low - Low</td>
<td>34 (9.58)</td>
<td>41 (11.55)</td>
<td>50 (14.08)</td>
<td>43 (12.11)</td>
<td>42 (11.83)</td>
</tr>
<tr>
<td>High - High</td>
<td>22 (6.2)</td>
<td>17 (4.79)</td>
<td>19 (5.35)</td>
<td>21 (5.92)</td>
<td>27 (7.61)</td>
</tr>
<tr>
<td>Non-significant</td>
<td>288</td>
<td>281</td>
<td>271</td>
<td>281</td>
<td>277</td>
</tr>
<tr>
<td>(non-clustered)</td>
<td>(81.13)</td>
<td>(79.15)</td>
<td>(76.34)</td>
<td>(78.87)</td>
<td>(76.9)</td>
</tr>
<tr>
<td>High - Low</td>
<td>2 (0.56)</td>
<td>4 (1.13)</td>
<td>3 (0.85)</td>
<td>5 (1.41)</td>
<td>2 (0.56)</td>
</tr>
<tr>
<td>Low - High</td>
<td>9 (2.54)</td>
<td>12 (3.38)</td>
<td>12 (3.38)</td>
<td>6 (1.69)</td>
<td>11 (3.1)</td>
</tr>
<tr>
<td>Total</td>
<td>355 (100)</td>
<td>355 (100)</td>
<td>355 (100)</td>
<td>355 (100)</td>
<td>355 (100)</td>
</tr>
<tr>
<td>Median crime rate</td>
<td>140.87</td>
<td>151.19</td>
<td>130.80</td>
<td>114.65</td>
<td>135.75</td>
</tr>
</tbody>
</table>

Note. Units = jurisdiction years (355 jurisdictions, 9 years, 2000-2008).

### Table 2

<table>
<thead>
<tr>
<th>Outcome category</th>
<th>n</th>
<th>Violent crime rate, 2000-2008</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Low - Low</td>
<td>371</td>
<td>101.50</td>
</tr>
<tr>
<td>High - High</td>
<td>196</td>
<td>919.44</td>
</tr>
<tr>
<td>Non-clustered</td>
<td>2,514</td>
<td>214.89</td>
</tr>
<tr>
<td>Mixed</td>
<td>114</td>
<td>220.67</td>
</tr>
</tbody>
</table>

Note. Data are from nine years, 355 jurisdictions. Mixed category includes both high surrounded by low and low surrounded by high.
Geographic patterning of local violent crime clusters

Maps of local crime clusters for each year appear in online Appendix A. As might be expected, Philadelphia and the city of Camden consistently form the nucleus of a high-high violent crime cluster at the center of the region. For all years, that high-high cluster extends to small jurisdictions southwest of Philadelphia, and in some years (2000, 2004, 2005) that extension includes the city of Chester and beyond. In other years, Chester and its surrounding jurisdictions form their own separate high-high local violent crime cluster.

For every year in the series, multiple low-low violent crime local clusters appear in Bucks, Montgomery, and Chester counties on the Pennsylvania side. In some years these clusters are bigger, fewer in number, and span county boundaries. In other years the clusters are smaller and more numerous. Given Messner and Anselin’s (2004) findings in the St. Louis metro area, it is noteworthy that these low-low clusters were not located at the very periphery of the metro area. Rather, they sometimes had inner edges just a jurisdiction or two away from Philadelphia and often had outer edges one to three jurisdictions from the edge of the metro area. It was only in northernmost Bucks County that one low-low cluster consistently included outermost jurisdictions.

The mixed local crime clusters were mostly low surrounded by high clusters. Instances of this type most frequently appeared adjacent to Philadelphia and often had outer edges one to three jurisdictions from that one low-low cluster consistently included outermost jurisdictions.

Consistency of cluster classification over time

To gauge the extent to which jurisdictions over the period received similar cluster classifications from year to year, kappa was used (Cohen, 1960). Following Fleiss (1981), coefficients at or above .75 indicate “good to excellent” agreement; from .40 to .75 indicate “reasonable” agreement, and from 0 to .40 indicate “no to poor agreement.” A kappa coefficient is given for each classification in the outcome, contrasting each cluster type, or non-clustered, against all other outcomes. Further, a combined kappa provides a weighted average value across all classifications.

Results appear in Table 4. Overall consistency across all classifications was reasonable (κ = .60). Consistency was in the good to excellent range for high-high cluster membership (κ = .77) and slightly lower, in the reasonable range, for the low-low (κ = .55) and the non-clustered (κ = .63) categories. Mixed cluster status exhibited poor consistency across years (κ = .34). In short, consistency across years seems at least reasonable for the two theoretical local crime clusters of most interest, the high-high and the low-low clusters.

Structural covariates

Controlling for time and area, the first multinomial model examined links between cluster classification and structural features of the focal jurisdiction. To consider the role of concentration effects, a separate model with each structural predictor considered separately in spatially lagged form was conducted. Multicollinearity prohibited including the same variable in focal and spatially lagged form in the same model. Since each binary contrast of local crime cluster classifications was considered four times, a Bonferroni adjusted alpha level of .0125 was used.

Model comparisons relied on differences in Bayesian Information Criterion (BIC) values (Raftery, 1995). BIC values take into account both model fit and complexity with lower values reflecting a better combination of fit and model parsimony. Differences in BIC values greater than 10 reflect “very strong” evidence that one model is preferred, while differences from 6 to 10 reflect “strong” evidence, and between 2 and 6 “positive” evidence of a preferred model (Long, 1997, p. 112).

Focal predictors

The model with focal structural predictors, and also controlling for area and linear temporal trend, represented a significant improvement over the null model (BIC = 2886.88; BIC difference > 500). Results appear in Table 5.

For the contrast between high-high and un-clustered jurisdictions (upper portion of table), all structural covariates connected with the outcome in the direction anticipated by the basic systemic model of crime and the racial-spatial divide literature. The odds of high-high vs. un-clustered classification were higher in lower SES, less residential stable, and less predominantly white jurisdictions. That said, only the significance of SES (p < .001) exceeded the adjusted alpha level.

For the contrast between low-low and un-clustered jurisdiction years (middle portion of table), higher SES (p < .001) and residential stability (p < .001) each were associated with a significantly greater likelihood of a jurisdiction year being classified low-low rather than unclustered.

For the contrast between mixed violent crime and un-clustered jurisdiction years (lower portion of table), none of the structural covariates linked to the outcome at even the conventional (p < .05) alpha level.

Results so far simultaneously agree and disagree with the structural links observed by Andresen (2011) at the CBG level. Both studies find expected SES and residential stability links for low-low contrasts with

<table>
<thead>
<tr>
<th>Table 4</th>
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</thead>
<tbody>
<tr>
<td>Consistency of cluster classification across years</td>
</tr>
<tr>
<td>Value</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>Overall agreement</td>
</tr>
</tbody>
</table>

Note: N = 355 jurisdictions across 9 years (2000-2008). Each year was treated as a different rater.
un-clustered. But in contrast to Andreason's (2011) results, the current work linked three features of community demographic fabric in the theoretically expected direction with contrasts between high-high and un-clustered units, although not all of the links were significant at the adjusted alpha level. Also in contrast to his work, the current work found no significant connections with mixed vs. un-clustered classification status.

Spatially lagged predictors

Results with spatially lagged status appear in Table 6 (BIC = 2635.12), lagged stability in Table 7 (BIC = 2701.244), and lagged racial composition in Table 8 (BIC = 2644.34). Given the BIC values, all three of these lagged models provided much better fit than the focal model (all BIC differences greater than -185). Further, among lagged models, those with either lagged status (BIC difference = -66) or lagged race (BIC difference = -57) proved preferable to the lagged stability model. Finally, the lagged SES model provided “strong” evidence of better fit compared to the lagged race model (BIC difference = -9). In line with the resource deprivation literature but disagreeing with the racial-spatial divide literature, it appeared that for models with just one concentration effect, spatially lagged SES proved noticeably more influential for this outcome than spatially lagged racial composition.

In each lagged model, the spatially lagged predictor linked significantly (p < .001) to each of the three outcome contrasts. Further, a higher surrounding SES, a more residually stable surround, and a more predominantly white surround connected in different models with lower probabilities of high-high classification, higher probabilities of low-low classification, and lower probabilities of a mixed classification. Lagged SES and lagged residential stability operated as expected given the basic systemic model of crime, and lagged racial composition operated as expected given the racial-spatial divide.

The relative influence of lagged SES vs. lagged racial composition can be gauged by considering the impact of a standard deviation change of each (SD = .73 for lagged SES; .62 for lagged racial composition) on the

Table 7
Predicting cluster membership: structure and lagged stability

<table>
<thead>
<tr>
<th></th>
<th>Contrast: High - High</th>
<th>Contrast: Low - Low</th>
<th>Contrast: Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-3.437</td>
<td>-3.120</td>
<td>-2.139</td>
</tr>
<tr>
<td>Time</td>
<td>0.019</td>
<td>-0.110</td>
<td>-0.050</td>
</tr>
<tr>
<td>Status</td>
<td>0.405</td>
<td>2.970</td>
<td>0.894</td>
</tr>
<tr>
<td>Lagged stability</td>
<td>-3.657</td>
<td>1.195</td>
<td>-1.409</td>
</tr>
<tr>
<td>Percent white</td>
<td>-0.028</td>
<td>-0.008</td>
<td>-0.019</td>
</tr>
<tr>
<td>Area</td>
<td>0.013</td>
<td>0.016</td>
<td>-0.029</td>
</tr>
</tbody>
</table>

Note: Results from a multilevel, multinomial model. Annual scores (n = 3,195) on the outcome and predictor variables nested within jurisdictions (n = 355). Reference category includes low violent rate jurisdictions surrounded by other low violent crime rate jurisdictions. Years = 2000-2008.

Table 8
Predicting cluster membership: structure and lagged percent white

<table>
<thead>
<tr>
<th></th>
<th>Contrast: High - High</th>
<th>Contrast: Low - Low</th>
<th>Contrast: Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-6.141</td>
<td>-4.095</td>
<td>-4.387</td>
</tr>
<tr>
<td>Time</td>
<td>0.051</td>
<td>-0.083</td>
<td>-0.031</td>
</tr>
<tr>
<td>Status</td>
<td>-0.781</td>
<td>2.302</td>
<td>0.871</td>
</tr>
<tr>
<td>Lagged percent white</td>
<td>-2.903</td>
<td>2.347</td>
<td>1.195</td>
</tr>
<tr>
<td>Area</td>
<td>0.004</td>
<td>0.012</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Note: Results from a multilevel, multinomial model. Annual scores (n = 3,195) on the outcome and predictor variables nested within jurisdictions (n = 355). Reference category includes low violent rate jurisdictions surrounded by other low violent crime rate jurisdictions. Years = 2000-2008.
classified as high-high vs. unclustered were 92 percent lower if the jurisdiction-year was one standard deviation higher on SES. For lagged racial composition, the corresponding odds were \((1 - \exp(-2.90 \times 0.62)) = 1 - 0.17\). A jurisdiction-year which was a standard deviation higher on spatially lagged racial composition, i.e., a standard deviation more white, had odds that were 83 percent lower that it would be classified as high-high vs. unclustered. Although the SES impact was somewhat stronger, the corresponding odds were (1 - exp(-2.90 \times 0.62)) = 1 - 0.17.

Consistency of classification across years was quite strong (k > .75) for the high-high clusters, and lower but still reasonable for the low-low clusters. Given the jurisdictions most likely to be classified as high-high were typically centrally located urban cores (Philadelphia, Camden, Chester), and their neighbors, the strong consistency of this classification speaks to the enduring contributions of the local and regional histories, demographies, and geographies of these places to the wider spatial patterning of structural and social problem inequalities. Given the historical development of this metropolitan area, its economic and demographic shifts in the last four decades, and the structure of its basic highway network, and comparable work in other metropolitan regions (Messner & Anselin, 2004), the location of these sub-regions of relatively high violence were largely as expected (Groff et al., 2014). The notable but not quite as strong consistency of low-low clusters suggests shifts in crime patterning in the inner ring to outer ring portions of the metropolitan area are taking place within an overarching frame of some stability in nearby violence levels. Reasons why the low-low clusters surfaced more often on the Pennsylvania rather than the New Jersey side of the metro region remain to be determined. Road and transportation network differences (Groff et al., 2014), or some type of state difference (Deane, Messner, Stucky, McGeever, & Kubrin, 2008), or numerous other features could prove relevant.

**Discussion**

The current work presents the first known, geographically complete, multi-year, theory-testing examination of violent crime sub-regions within a large and complex metropolitan area. Three concerns directed the investigation. If jurisdiction-level local violent crime clusters can be identified, which seen likely given previous intra-metropolitan (Messner & Anselin, 2004) and intra-city (Andresen, 2011) work, how consistent are these classifications over most of a decade? Further, do the three demographic core community features relevant to both the basic systemic model of crime (Bursik & Grasmick, 1993) and the racial-spatial divide (Peterson & Krivo, 2010) prove relevant to different types of sub-region membership in the theoretically expected directions? And finally, given extensive work on spatial concentration effects due to either socioeconomic factors or racial composition, are both features of a jurisdiction’s immediate neighbors equally relevant to type of violent crime sub-region membership?

The analyses presented here observed different types of violent crime sub-regions across the Philadelphia-Camden metropolitan region. The most typical type of sub-region, aside from un-clustered jurisdictions, were zones of relatively low levels of violent crime (low-low local clusters), followed by zones of relative susceptibility to violent crime (high-high local clusters). Mixed regions presenting disparate crime levels (low surrounded by high or high surrounded by low local clusters) were the least frequent types of local cluster.
of each to the character of violence in and around the ecological unit was considered. Results suggested for this outcome lagged SES was somewhat more influential. The model with lagged SES provided the best fitting model, and the impact on the odds of being in a high-high cluster vs. no cluster was slightly larger for a standard deviation shift on lagged SES vs. a comparable shift on lagged racial composition. But the differences in impact were minor in comparison to the overall size of each lagged impact. Both the surrounding economic and racial composition influences were critical. To learn more about specifying how each of these two aspects specifically shape crime patterns requires separating the two. This is not routinely done, making such specification more difficult (Massey, 1998). The empirical ecological overlap between SES and race (Peterson & Krivo, 2010) creates further difficulties.

From a practical perspective, the current work has one general implication for future studies of intra-metropolitan crime patterning. Intra-metropolitan crime investigations at the jurisdiction level clearly need to model complete geographical surfaces so that spatial patterning can be estimated and taken into account when examining jurisdiction-level crime. Otherwise, studies based on incomplete intra-metropolitan crime data (e.g., Kneebone & Raphael, 2011) run the risk of misspecifying links between demographic structure and crime at the jurisdiction level. The current study of course has limitations. Only one approach to local clustering was used. There are others, and different approaches can sometimes yield different patterns (Hanson & Wieczorek, 2002; Linton, Jennings, Latkin, Gomez, & Mehta, 2014; Rashidi et al., 2015). Another limitation, shared with Andresen (2011), is that the models do not explicitly account for the spatial autocorrelation while predicting the discrete choice outcome. Some highly technical work by Miyamoto, Vichiensan, Shimomura, and Páez (2004) in transportation has made such a separation. But, as Andresen (2011) also pointed out, in Miyamoto et al’s (2004) simulation results explanatory coefficients were smaller for the model that did not consider spatial autocorrelation than they were in the three different models that did. Folding in spatial autoregressive parameters in these types of local cluster models seems an important future avenue. Partially counterbalancing these limitations are several strengths including crime data across all jurisdictions in a large metropolitan area, data over almost an entire decade, indices for SES and residential stability with strong internal consistency, and an appropriate multilevel/mixed effects model.

In short, the current work documents local violent crime clusters in a large metropolitan region, finding that specific sub-region classifications prove generally consistent for jurisdictions across nine years of a decade. Further, as anticipated by the front half of the basic systemic model of crime, focal jurisdiction SES and residential stability link as expected to membership in sub-regions that are safer than average locally, and more dangerous than average locally. In line with work on crime concentration effects, spatially lagged SES significantly affects all three sub-region contrasts with un-clustered jurisdictions, and in line with work on the racial- spatial divide, spatially lagged racial composition also significantly affects all three contrasts in the anticipated direction. Crucial questions about which specific dynamics mediate the shaping impacts of demographic setting conditions on sub-regional local crime patterning remain.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jcrimjus.2015.03.002.

Notes

1. Andresen (2011) suggests the demographic covariates included were “representing social disorganization” (p. 396). This statement reflects the substantial semantic ambiguity that exists about this construct and thus its operationalization (see Taylor, 2015: 207–210).

2. A full 62% of all blacks in the United States live in highly segregated metropolitan areas, with the separate black and white neighborhoods in these areas providing distinct social environments. Indeed, whites live almost exclusively in highly advantaged neighborhoods, while blacks and Latinos reside in highly disadvantaged local communities. This combined process of segregation and ethnoracial conditions provides the basic structural context within which people of different races and ethnicities live and social problems play out” (Krivo et al., 2009: 1766).

3. quickfacts.census.gov; county totals retrieved July 12, 2014; calculations by the authors.

4. Law enforcement coverage across the Philadelphia metro region is complicated. Many municipalities are covered in part or wholly by their respective state police agency. Further, the different state police agencies report crime differently for places they cover in whole or in part. For a couple dozen smaller Pennsylvania municipalities this required some estimation (Taylor, Groff, Elesh, & Johnson, 2014).

5. Each location has its own value of a local Moran’s I. The significance – technically pseudo-significance because simulation is used – uses a conditional type of random permutation test (Anselin, 1995; Bailey & Gatrell, 1995). For each location, holding that one location constant, the set data values of is randomly permuted a large number of times. The fraction of simulations generating a LISA statistic as or more extreme than the one observed at that specific location reflects the pseudo-significance level. So if out of 99 simulations only 4 simulations generated a value as or more extreme than the one observed for that location, the pseudo-significance level would be p < .05. In this case 999 random permutations were specified. The program also allows for an Empirical Bayes (EB) adjustment as the surrounding rates are averaged. This feature seems desirable since jurisdictions can vary so much in population size. The EB adjustment works by comparing values on a variable for a jurisdiction to the grand mean. Values deviating more substantially from the grand mean are therefore adjusted somewhat toward the mean. “The principle is referred to as shrinkage, in the sense that the raw rate is moved (shrunken) towards an overall mean: an inverse function of the inherent variance” (Anselin, Kim, & Sybri, 2004, p. 201). Here, the EB correction has been applied to violent crime rates for the Moran’s I clustering analysis.


7. Placing married couple households with more obvious stability indicators is appropriate. Earlier analyses at the census tract level have labeled this variable “familism” and have included marital status with stability (Hunter, 1971).

8. LGLAMMS are a class of multilevel latent variable models for (multivariate) re sponses of mixed type including continuous responses, counts, duration/survival data, dichotomous, ordered and unordered categorical responses and rankings” (Rabe-Hesketh, Skrondal, & Pickles, 2004, p. 1).

9. In essence, this approach treats the consistency as an inter-rater reliability problem, where each year “rates” each jurisdiction on the outcome.

10. These are obtained using the gllappred command with options mu and marginal.

11. The reverse does not hold; high-high clusters do not present like mixed clusters.

12. Messner and Anselin’s (2004) analysis of homicide sub-regions in the St. Louis metro region was exploratory and focused only on homicide.

References


