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

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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.

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

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(2014) examined how land use and street network factors shaped adjacency impacts. Jurisdictions with more permeable boundaries proved more susceptible in some years to increasing violent or property crime if surrounded initially by higher crime locales.

Such a finding aligns with a diffusion model (Messner & Anselin, 2004) for explaining adjacency impacts. This model was supported by Messner and Anselin's (2004) exploratory county-level spatial analyses of homicide rates in the St. Louis metropolitan area at two points in time from the mid-1980s to the mid-1990s. They identified local clusters of counties using LISA statistics (Anselin, 1995) and found both stability 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 comparable 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 socioeconomic 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 expected 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 cluster demographic links, and the high-surrounded-by-low 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 unaddressed, 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 earlier 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 jurisdictions, being surrounded by structurally similar jurisdictions can intensify 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 structurally 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 geographic 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 (Peterson & Krivo, 2010, p. 99). Spatially lagged structural disadvantage 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 earlier works finding significant impacts of surrounding levels of disadvantage 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 communities, 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 autocorrelation, Peterson and Krivo's (2010) research suggests that lagged racial composition 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 jurisdictions 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 jurisdictions nearby some of these locales have experienced withdrawal of capital even prior to racial and economic shifts (Smith, Caris, & Wyly, 2001). Other suburban jurisdictions have been or are extremely well off economically (Adams et al., 2008). Road and rail transport systems combined 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 drifted 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 low-low local clusters of violent crime. Messner and Anselin's (2004) 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 suggest such a geographic arrangement.

Community structure as an organizing frame

Bursik and Grasmick's (1993) basic systemic model of crime highlights the relevance of three structural precursors of crime- and delinquency-related social and cultural dynamics: community socioeconomic 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.[3] 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.[4] 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.[5] 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 [6] 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).[7] 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

Table 1
Violent crime cluster categorizations, by year

Outcome	2000	2001	2002	2003	2004	2005	2006	2007	2008	Total
Low - Low	34 (9.58)	41 (11.55)	50 (14.08)	43 (12.11)	42 (11.83)	40 (11.27)	40 (11.27)	41 (11.55)	40 (11.27)	371 (11.61)
High - High	22 (6.2)	17 (4.79)	19 (5.35)	21 (5.92)	27 (7.61)	23 (6.48)	23 (6.48)	23 (6.48)	21 (5.92)	196 (6.13)
Non-significant	288	281	271	280	273	277	281	281	282	2,514
(non-clustered)	(81.13)	(79.15)	(76.34)	(78.87)	(76.9)	(78.03)	(79.15)	(79.15)	(79.44)	(78.69)
High - Low	2 (0.56)	4 (1.13)	3 (0.85)	5 (1.41)	2 (0.56)	5 (1.41)	4 (1.13)	4 (1.13)	5 (1.41)	34 (1.06)
Low - High	9 (2.54)	12 (3.38)	12 (3.38)	6 (1.69)	11 (3.1)	10 (2.82)	7 (1.97)	6 (1.69)	7 (1.97)	80 (2.5)
Total	355 (100)	355 (100)	355 (100)	355 (100)	355 (100)	355 (100)	355 (100)	355 (100)	355 (100)	3,195 (100)
Median crime rate	140.87	151.19	130.80	114.65	135.75	128.22	129.18	142.55	153.22	138.26

spatial size, and the likelihood that larger jurisdictions are adjacent to more jurisdictions than smaller ones.

Analytic approach

Multilevel/mixed effects multinomial logistic regression models were used with demographic predictors and violent crime cluster classifications as the outcome. Years were nested within municipalities. Random intercepts for each jurisdiction for each binary contrast were included. Municipality-specific random effects “accommodate longitudinal dependence” in the outcome data over time and represent “unobserved heterogeneity” across municipalities (Rabe-Hesketh & Skrondal, 2012b, p. 659). The effects for specific predictors are therefore 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 (Long & Freese, 2006).

Throughout the modeling process, the municipality-year category of non-clustered was the reference 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 surrounded by other high violent crime jurisdictions.

Clusters of high – low (n = 34) and low – high (n = 80) jurisdiction-years appeared relatively infrequently (1% and 3%, respectively). Regardless of the focal/surrounding jurisdiction relationship, both of 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 2
Descriptive crime statistics by cluster type

Outcome category	n	Violent crime rates, 2000-2008				
		Mean	SD	Median	Min	Max
Low-Low	371	101.50	58.88	90.52	0.00	268.13
High-High	196	919.44	785.28	637.30	251.71	4,398.26
Non-clustered	2,514	214.89	234.60	136.20	0.00	2,059.42
Mixed	114	220.67	164.84	193.61	0.00	928.38

Note. Data are from nine years, 355 jurisdictions. Mixed category includes both high surrounded by low and low surrounded by high.

Table 3
Descriptive statistics for time-varying covariates

Time-varying covariates	n	Mean	SD	Min	Max
Socieconomic status (SES)	3,195	0.00	0.72	-4.16	1.77
Residential stability	3,195	0.00	0.85	-2.73	1.79
Percent white	3,195	87.07	15.39	0.00	100.00
Violent crime rate	3,195	245.15	336.68	0.00	4398.26
Spatially lagged status	3,195	0.07	0.73	-2.66	1.80
Spatially lagged stability	3,195	0.14	0.65	-2.37	1.57
Spatially lagged percent white	3,195	-0.02	0.62	-2.40	0.82

Note. Units = jurisdiction years (355 jurisdictions, 9 years, 2000-2008). SES and stability are indices; higher scores indicate higher status or greater residential stability. Spatially lagged predictors based on first order queen contiguity, EB weighting.

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 southeast Philadelphia on the New Jersey side, or adjacent to or further down from southwestern Philadelphia on the Pennsylvania side.

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).[9] 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 ($\kappa = .60$). Consistency was in the good to excellent range for high-high cluster membership ($\kappa = .77$) and slightly lower, in the reasonable range, for the low-low ($\kappa = .55$) and the non-clustered ($\kappa = .63$) categories. Mixed cluster status exhibited poor consistency across years ($\kappa = .34$). 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 residentially 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 4
Consistency of cluster classification across years

Value	Category	Kappa	z	p <
1	Non-clustered	0.631	71.33	.001
2	High-High	0.765	86.47	.001
3	Low-Low	0.549	62.11	.001
4	Mixed	0.336	37.98	.001
Overall agreement		0.601	95.67	.001

Note: N = 355 jurisdictions across 9 years (2000-2008). Each year was treated as a different rater.

Table 5
Predicting cluster membership using structural variables

	b	SE	OR	p
Contrast 1: High - High				
Intercept	-3.312	0.804	0.036	0.000
Time	0.061	0.043	1.063	0.155
Status	-1.286	0.262	0.276	0.000
Stability	-0.400	0.199	0.670	0.045
Percent white	-0.021	0.008	0.980	0.014
Area	-0.007	0.007	0.994	0.357
Contrast 2: Low - Low				
Intercept	-4.145	1.260	0.016	0.001
Time	-0.102	0.033	0.903	0.002
Status	2.776	0.304	16.052	0.000
Stability	0.798	0.182	2.220	0.000
Percent white	0.008	0.014	1.008	0.552
Area	0.002	0.009	1.002	0.850
Contrast 3: Mixed				
Intercept	-3.435	0.870	0.032	0.000
Time	-0.020	0.045	0.980	0.661
Status	-0.065	0.283	0.937	0.818
Stability	-0.354	0.202	0.702	0.080
Percent white	-0.010	0.009	0.990	0.271
Area	-0.020	0.013	0.981	0.137
AIC	2771.565			
BIC	2886.883			
Log-likelihood	-1366.783			
Level 2				
var(1): 5.763 (.452)				

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.

un-clustered. But in contrast to Andresen'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 residentially 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 odds that a jurisdiction- year is classified as high-high vs. un-clustered. For lagged SES, the impact on those odds was (1- (exp(-3.39*.73))) = 1-.084. The odds that a jurisdiction year would be

Table 7
Predicting cluster membership: structure and lagged stability

	b	SE	OR	p
Contrast 1: High - High				
Intercept	-3.437	0.878	0.032	0.000
Time	0.019	0.050	1.020	0.698
Status	0.405	0.254	1.499	0.111
Lagged stability	-3.657	0.344	0.026	0.000
Percent white	-0.028	0.009	0.972	0.002
Area	0.013	0.008	1.013	0.094
Contrast 2: Low - Low				
Intercept	-3.120	1.377	0.044	0.023
Time	-0.110	0.033	0.896	0.001
Status	2.970	0.303	19.501	0.000
Lagged stability	1.195	0.296	3.305	0.000
Percent white	-0.008	0.016	0.992	0.618
Area	0.016	0.009	1.016	0.080
Contrast 3: Mixed				
Intercept	-2.139	0.861	0.118	0.013
Time	-0.050	0.045	0.951	0.266
Status	0.894	0.262	2.445	0.001
Lagged stability	-1.409	0.248	0.244	0.000
Percent white	-0.019	0.009	0.981	0.032
Area	-0.029	0.018	0.972	0.103
AIC	2585.926			
BIC	2701.244			
Log-likelihood	-1273.963			
Level 2				
var(1): 4.954 (.436)				

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 6
Predicting cluster membership: structure and lagged status

	b	SE	OR	p
Contrast 1: High - High				
Intercept	-2.807	0.944	0.060	0.003
Time	0.037	0.050	1.038	0.462
Lagged status	-3.392	0.332	0.034	0.000
Stability	-0.471	0.252	0.625	0.062
Percent white	-0.041	0.010	0.959	0.000
Area	0.007	0.009	1.007	0.383
Contrast 2: Low - Low				
Intercept	-5.075	1.183	0.006	0.000
Time	0.009	0.031	1.009	0.764
Lagged status	1.383	0.196	3.985	0.000
Stability	0.374	0.140	1.454	0.007
Percent white	0.006	0.013	1.006	0.641
Area	0.014	0.009	1.014	0.104
Contrast 3: Mixed				
Intercept	-2.201	0.924	0.111	0.017
Time	-0.018	0.044	0.982	0.684
Lagged status	-1.255	0.206	0.285	0.000
Stability	-0.596	0.208	0.551	0.004
Percent white	-0.025	0.010	0.976	0.015
Area	-0.032	0.017	0.968	0.054
AIC	2519.805			
BIC	2635.122			
Log-likelihood	-1240.902			
Level 2				
var(1): 4.757 (.412)				

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

	b	SE	OR	p
Contrast 1: High - High				
Intercept	-6.141	0.340	0.002	0.000
Time	0.051	0.050	1.052	0.311
Status	-0.781	0.261	0.458	0.003
Stability	-0.152	0.253	0.859	0.548
Lagged percent white	-2.903	0.261	0.055	0.000
Area	0.004	0.009	1.004	0.621
Contrast 2: Low - Low				
Intercept	-4.095	0.266	0.017	0.000
Time	-0.083	0.033	0.920	0.011
Status	2.302	0.274	9.998	0.000
Stability	0.677	0.251	1.968	0.007
Lagged percent white	2.347	0.507	10.455	0.000
Area	0.012	0.012	1.012	0.310
Contrast 3: Mixed				
Intercept	-4.387	0.280	0.012	0.000
Time	-0.031	0.046	0.970	0.498
Status	0.271	0.243	1.311	0.264
Stability	-0.354	0.225	0.702	0.115
Lagged percent white	-1.305	0.236	0.271	0.000
Area	-0.016	0.014	0.984	0.253
AIC	2529.023			
BIC	2644.340			
Log-likelihood	-1245.511			
Level 2				
var(1): 5.279 (.436)				

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*.62)) = 1-.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 more important point is that these two spatially lagged impacts were quite powerful. By contrast, a standard deviation increase in residential stability, albeit highly significant, only lowered the odds of a high-high vs. un clustered classification by nine percent.

Classification using the best fitting model

Looking at results from the best fitting of these models, the one with spatially lagged status, and population averaged or marginal predicted classification probabilities (Rabe-Hesketh & Skrondal, 2012a), provides a closer picture of model predictions for the different contrasts.[10] Jurisdiction-years classified high-high had an average predicted high-high probability of .42. This average was significantly higher (all ps < .001 by post hoc Scheffe test) than the average predicted high-high probability for all other jurisdiction-year classifications. Average predicted high-high probabilities = .16, .03 and .001 for, respectively, mixed, un-clustered, and low-low jurisdiction-years. Jurisdiction-years classified low-low had an average predicted low-low probability of .13. This average was significantly higher (all ps < .001 by post hoc Scheffe test) than the average predicted low-low probability for all other jurisdiction-year classifications. Average predicted low-low probabilities = .07, .04 and .004 for, respectively, un-clustered, mixed, and high-high jurisdiction-years. Jurisdiction-years classified as mixed had an average predicted mixed probability of .06. This was not significantly different from the average mixed probability for jurisdiction-years classified as high-high (.07; ns by Scheffe test). But it was significantly higher (ps < .001 by Scheffe test) than the average predicted mixed probability for un-clustered (average predicted probability = .04) and low-low (average predicted probability = .01) jurisdiction-years. These classification results agree with Andresen's (2011) findings in that the mixed clusters present like high-high clusters; the predicted probability of a mixed classification was comparable for mixed and high-high jurisdiction-years.[11]

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.[12] Three concerns directed the investigation. If jurisdiction-level local violent crime clusters can be identified, which seemed 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.

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.

Focal jurisdiction demographics linked to sub-region type in the manner expected by the basic systemic model of crime (Bursik & Grasmick, 1993). Higher SES connected cleanly to lower chances of being in a relatively higher violence sub-region, and higher chances of being in a sub-region relatively low violence. Stronger residential stability similarly increased chances of membership in a sub-region of low relative violence. Focal jurisdiction racial composition, however, did not connect to either outcome at the adjusted significance level. Although Andresen (2011) used different theoretical frames than applied here, the substance of many of the demographic indicators overlap across the two studies. Whether our finding of more theoretically consistent links than he observed is due to different ecological units, different specific variables, different locations, different conditions in matrices of predictors, or something else, is not clear at this time.

Although focal racial composition linked in the expected way to only one outcome contrast (high-high vs. un-clustered), and then only at the conventional rather than adjusted alpha level, in line with Peterson and Krivo's (2010) work on the racial-spatial divide, *spatially lagged* racial composition connected powerfully (p < .001) to all three outcome contrasts. Jurisdictions surrounded by more predominantly white jurisdictions had markedly higher chances of being in a sub-region of relatively low violent crime, markedly lower chances of being in a sub-region of relatively high violent crime, and markedly lower chances of being in a sub-region experiencing mixed levels of violence. These findings with spatially lagged racial composition and violence extend Peterson and Krivo's (2010) research in two ways. They suggest the relationship is generalizable to membership in metro sub-regions of relative violence, not just intra-city regions. Further, the link applies when violent crime over most of a decade is considered, rather than just one three-year average.

Thus, across a metro region, as well as within cities, "proximity to the structural privileges associated with whites is critical in gaining access to the social, political, and economic resources that distance communities from threats to safety and keep violence low" (Peterson & Krivo, 2010, p. 100). A critical task for future investigations is to unearth the social, political, and economic dynamics *behind* these proximity impacts. Conflict-oriented accounts of the social production of urban and metropolitan spatial inequalities may prove useful for framing such inquiries (Gottdiener, 1994; Logan & Molotch, 1987).

Another question left open by Peterson and Krivo's (2010) work was the relative contribution of spatially lagged SES vs. spatially lagged race. Here, rather than asking about relative contributions of each to violent crime rates in the focal ecological unit, contributions 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.

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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 combination of segregation and ethnoracial differentials in social and economic 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 data set of values is randomly permutated a large number of times. The fraction of simulations generating a LISA statistic as or more extreme than the one observed for 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 (shrunk) towards an overall mean, as an inverse function of the inherent variance" (Anselin, Kim, & Syabri, 2004, p. 201). Here, the EB correction has been applied to violent crime rates for the Moran's *I* clustering analysis.

[6] GeoLytics methodology can be found at http://www.geolytics.com/USCensus,Annual-Estimates-2001-2005,Data,Methodology,Products.asp.

[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] "GLLAMMS are a class of multilevel latent variable models for (multivariate) responses 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 gllapred 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.

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