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Living on the Edge: Neighborhood Boundaries and the Spatial Dynamics of Violent Crime

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Abstract Neighborhood boundaries are a defining aspect of highly segregated urban areas. Yet, few studies examine the particular challenges and spatial processes that occur at the bordering region between two neighborhoods. Extending the growing literature on spatial interdependence, this article argues that neighborhood boundaries—defined as sharp changes in the racial or socioeconomic composition of neighborhoods—are a salient feature of the spatial structure with implications for violent crime and other outcomes. Boundaries lack the social control and cohesion of adjacent homogeneous areas, are contested between groups provoking intergroup conflict, and create opportunities for criminal behavior. This article presents evidence linking racial neighborhood boundaries to increased violent crime. The findings illustrate the importance of neighborhood boundaries for our understanding of spatial dimensions of population dynamics above and beyond the characteristics of neighborhoods.

Keywords Neighborhoods · Neighborhood boundaries · Crime · Segregation · Spatial inequality

Introduction

In 1945, St. Clair Drake and Horace R. Cayton argued in "Black Metropolis" (1945/1993:190) that "one consequence of the pattern of residential segregation is that an area of potential conflict has been created all around the boundaries of the Black Belt." More recently, Elijah Anderson (1990:154–156) reported about "the edge" in Eastern City (a pseudonym for his case study city) as "the place where two

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communities meet, where the lower-income black residents come in contact with the middle- and upper-income white ones." Pattillo (2007) described what residents call the "dividing" or "invisible" line in Chicago's South Side as an area that separates prospering South from languishing North Kenwood.

These ethnographic accounts illustrate the relevance of boundaries for spatial inequality and the distribution of populations across space as an important dimension of population research. Most quantitative research, however, has analyzed neighborhoods as independent units without considering the broader sociospatial structure. A rapidly growing literature has addressed this problem, moving beyond the treatment of neighborhoods as isolated islands.[1] This work has considered proximity and dependencies between geographic areas as a key component of spatial inequality (Morenoff and Sampson 1997; Sampson et al. 1999; Sharkey 2014). But what are particular challenges and spatial processes that occur at bordering regions between two neighborhoods? The emerging literature on spatial dependencies ignores that substantial racial and socioeconomic segregation creates areas of transition between relative homogeneous zones. These transitions are more or less spatially abrupt, with potential consequences for those residing nearby. Extending previous work on spatial interdependence, I argue that these boundaries are an important aspect of the sociospatial structure with implications for crime and a range of different outcomes.

For this end, I first elaborate a theoretical argument about the particular challenges and processes that occur at social neighborhood boundaries. Like "the edge" in Eastern City and the "dividing line" in Chicago's South Side, social boundaries capture the transition from a low-class to a high-class neighborhood or from a predominantly white to a Hispanic area. They are related to symbolic neighborhood boundaries defined as conceptual categorizations of space into distinct areas and to political boundaries defined as administrative borders that divide geographical areas into school districts, police precincts, congressional districts, or others. In contrast to physical boundaries, such as railways, major roads, or rivers, social neighborhood boundaries facilitate contact and potentially conflict between distinct groups. Building on social disorganization, group threat theories, and the concept of criminal opportunity, I argue that boundaries lack the social control and cohesion of adjacent homogeneous areas; are contested between groups, provoking intergroup conflict; and create opportunities for criminal behavior. As such, boundaries not only separate space into distinct areas but also influence a range of different outcomes.

To illustrate the importance of neighborhood boundaries, I present evidence linking racial neighborhood boundaries to increased violent crime. Using incident-level crime data from Chicago and negative binomial regressions, I show that violent crime is higher at neighborhood boundaries above and beyond the characteristics of a given neighborhood; common measures of spatial interdependence; and other types of boundaries, such as major roads, rivers, or school district borders. This relationship is consistent across different measures of crime, including incident-level police data, geocoded homicides, and perceived violence from survey data. These findings illustrate the importance of neighborhood boundaries for our understanding of a cardinal dimension of population science: that is, the distribution of populations across space.

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[1] Related research has attempted to overcome the limitations of predefined, mutually exclusive spatial units with nonoverlapping boundaries and instead has used alternative definitions of neighborhoods (Hipp et al. 2012; Sampson et al. 1997; Spielman and Logan 2013).

Neighborhood Boundaries

The "edge" in Eastern City and the "dividing line" in Chicago's South Side illustrate the importance of boundaries for spatial inequality. They have a structural, symbolic, and political dimension (Logan 2012). Social or structural neighborhood boundaries are based on compositional changes in the population. They capture the transition from a low-class to a high-class neighborhood or from a predominantly white to a Hispanic area. Symbolic (neighborhood) boundaries, in contrast, refer to the subjective separation of space into distinct areas. Following the broader boundary concept, symbolic boundaries are conceived as "conceptual distinctions made by social actors to categorize objects, people, practices, and even time and space" that "separate people into groups and generate feelings of similarity and group membership" (Lamont and Molnar 2002:168). Like "the edge" and the "dividing line," these socially constructed neighborhoods are partly based on social boundaries but also influence the selection of residents into neighborhoods. Campbell et al. (2009) study subjectively constructed neighborhood boundaries based on interviews with 37 adolescents and 33 parents (see also Hwang 2016). They found that ethnoracial compositions play a major role in how people define neighborhood boundaries. Political or administrative boundaries are limiting lines of jurisdictional authority for various levels of government, such as state borders and congressional or school districts. These borders can shape both social and symbolic neighborhood boundaries but might also be influenced by them. Redistricting of electoral district boundaries, for example, is often based on social boundaries, with lawsuits challenging controversial changes. Accordingly, social, symbolic, and political neighborhood boundaries are all intertwined and often overlap with physical boundaries, such as railways, major roads, or rivers (Kramer 2017).

Building on the idea that the physical environment creates criminal opportunities, previous research has linked physical and administrative boundaries to criminal behavior (Brantingham et al. 2009; Kim and Hipp 2017; Song et al. 2017). Kim and Hipp (2017), for example, examined this relationship using data from southern California. They showed that crime level is higher at physical (interstate highways, parks, and rivers) and city boundaries. Similarly, other work has found higher crime rates at spatial boundaries as defined by changes in land use classification (Song et al. 2017). This research highlights the importance of physical and administrative boundaries for crime.

In contrast, I focus here on social boundaries based on the distribution of the population across neighborhoods. Social boundaries are defined by changes in composition between adjacent areas. They can be sharp, with abrupt compositional changes that clearly separate space into distinct areas; and they can be soft or fuzzy, with extended zones of transition (Legewie and Schaeffer 2016; Logan 2012; Lynch 1960; Spielman and Logan 2013). Social neighborhood boundaries are closely linked to spatial segregation. They are located at the edges of highly segregated areas and are a defining aspect of urban life in the United States and in many countries across the world (Roberto 2015). As such, social neighborhood boundaries demarcate distinct areas and thereby create "organic" neighborhoods. Similar to physical barriers, such as railways, major roads, and rivers (Kim and Hipp 2017), Anderson's (1990) and

Pattillo's (2007) ethnographic accounts suggest that boundaries have consequences for those residing nearby, above and beyond demarcating distinct areas.[2] Other research has provided further support. Desmond and Valdez (2012), for example, found that the number of nuisance property citations is higher in areas at the boundary of black communities. They argue that this pattern is largely a result of nonblack residents who feel threatened by their black neighbors. Legewie and Schaeffer (2016) showed that the number of complaints about neighbors making noise, blocking the driveway, or drinking in public is higher at boundaries between ethnically homogeneous neighborhoods, a pattern they attribute to conflict between groups around contested boundaries.

At least two possible mechanisms explain why bordering regions at segregated locales are important for crime and possibly other outcomes. The first mechanism builds on *social disorganization theory* and the concept of collective efficacy (Sampson 2012; Sampson and Groves 1989; Sampson et al. 1997). Similar to areas with residential instability or ethnoracial heterogeneity, neighborhood boundaries defined by transitions between differently composed homogeneous areas are characterized by lower levels of informal social interactions, solidarity, and trust essential for building shared expectations about social control. At social neighborhood boundaries, different groups face each other, reducing social interactions, ties, and familiarity between neighbors. The boundary separates residents and lowers the level of cohesion and informal social control. The reduced level of social control and sense of guardians at neighborhood boundaries creates criminal opportunities, increasing the probability that motivated offenders will commit a crime. The interstitial location between cohesive communities fosters neglect for public goods and a reduced willingness to intervene on behalf of the common good. Drake and Cayton (1945/1993:190) described these areas as a "racial no man's land" with no cohesive neighborhood community. Suttles (1972) similarly described how urban communities are (socially) constructed around a core located at the center of neighborhood communities. As a consequence, the reduced level of social control and sense of guardians at neighborhood boundaries creates opportunities for offenders and increases the likelihood of crime.

Second, theories surrounding intergroup competition, group threat, and defended neighborhoods might explain the relevance of boundaries for crime and other outcomes (Blalock 1967; Blumer 1958; Olzak 1994; Suttles 1972). Similar to the in-migration of minority groups or the sizable presence of out-group members, proximity to neighborhood boundaries increases the perceived levels of threat and provokes intergroup conflict. Boundaries create a polarized setting where two groups face each other. The proximity to areas with a high concentration of out-group members confronts residents with the (perceived) competition over economic interests and nonmaterial issues, such as the prevailing way of life or the use of public space (Legewie and Schaeffer 2016). This argument resonates with a number of ethnographic studies from the *defended neighborhoods* perspective. Based on fieldwork observations in white urban

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[2] Also note Pattillo's later work (2013), in which she argued that members of the black middle class often reside at the boundary between white middle-class communities and poor black neighborhoods. This location influences the opportunities and disadvantages of the black middle class in important ways (see also Sharkey 2014).

neighborhoods, these studies describe how residents develop a sense of community identity that is based on the exclusion of out-groups and enforced through violence and other means (DeSena 1990; Rieder 1985; Suttles 1972). Along these lines, Andrews and Seguin (2015) argued (on a larger geographical scale) that group threat leads to collective mobilization in settings where a largely homogeneous area populated by residents from an allegedly threatened group is exposed to a proximate threatening group. Their argument is based on the idea that the dense concentration of a threatened group provides the foundation for mobilization against a proximate threatening group. Aside from fostering perceived threat, the boundary itself might be contested with conflicting claims about group turf, as in, for example, the race riots of the early twentieth century. Janowitz (1979:393) described the collective violence as "an interracial clash, an ecologically based struggle at the boundaries of the expanding black neighborhoods" related to the influx of African Americans as part of the Great Migration. Bergesen and Herman (1998:41) described the 1992 Los Angeles riots in similar terms. They found increased violence in the "contact zone" or "contested area" located between the Latino and African American communities (see also Grimshaw 1960). More recently, Legewie and Schaeffer (2016) asserted that zones of transition between areas populated by different groups are particularity prone to neighborhood conflict. These zones are contested areas in which perceived entitlement claims about the use of public space spill over from adjacent homogeneous communities into the bordering region. Ambiguities about group rank and perceived threat from out-group members fuel conflict that might translate to criminal behavior.

Together, these explanations elaborate the mechanisms by which social neighborhood boundaries influence various aspects of social life. Boundaries lack the social control and cohesion of adjacent homogeneous areas, increase the perception of threat, are contested between groups and thus provoke intergroup conflict, and create opportunities for crime. These processes are largely place-specific insofar as the reduced level of informal social control and opportunities for crime are tied to the bordering regions in which areas transition from one demographic group to another. As a consequence, I expect higher levels of violent crime at neighborhood boundaries.

Data and Methods

To examine the role of boundaries, I estimate the relationship between violent crimes and racial neighborhood boundaries in Chicago. The analysis is based on the census block level. It uses geocoded, incident-level crime data from the Chicago Police Department from 2011 combined with data on the census block and census block group level from the 2010 census and the 2007–2011 five-year estimates from the American Community Survey (ACS). Census blocks are the smallest geographic unit used by the Census Bureau and often refer to a single city block in a major metropolitan area. Chicago contains 46,311 census blocks, with an average population of 58.21 residents embedded in 811 census tracts. I restrict the sample to all populated census blocks and exclude public parks so that the final sample consists of 36,519 census blocks.

Estimation Strategy

The main analysis uses the number of violent crimes in 2011 reported by the Chicago Police Department on the census block level as the dependent variable and a measure of social neighborhood boundaries as the focal independent variable (see discussion below). To model aggregated crime incidents, I use negative binomial regressions—a common approach in research on crime (Osgood 2000). Negative binomial regressions are appropriate for count data confined to positive integers and allow for overdispersion across census blocks (Gelman and Hill 2007:115; Long and Freese 2005: chapter 8). I use clustered standard errors to account for the clustering of census blocks in block groups (with some control variables measured on the block group level) (Angrist and Pischke 2008: chapter 8.2). Formally, the model can be defined as

$$\lambda_{jg} = \exp\left(\alpha + \delta D_{jg} + \mathbf{X}_{jg}\boldsymbol{\beta}_1 + \mathbf{U}_g\boldsymbol{\beta}_2\right),$$

where j and g are indices for census blocks and block groups, respectively. D_{jg} refers to the measure of social neighborhood boundaries, and the coefficient δ estimates the relationship between neighborhood boundaries and crime. $\mathbf{X}_{jg}$ and $\mathbf{U}_g$ represent matrices of control variables on the census block and block group level. The two $\boldsymbol{\beta}$s are vectors of corresponding coefficients.

The negative binomial regressions model the number of crimes but do not standardize for a baseline (Hipp et al. 2011; Osgood 2000). To account for variations in the size of the population across areas, I include population size (in 100s) as a control variable and in supplementary analysis as an offset. Offset or exposure variables are defined as the natural logarithm of the population with a coefficient that is fixed to 1. They transform count models of crimes to models of per capita rates (Osgood 2000).

A limitation of this approach is the observational nature of the data. Although the analysis adjusts for internal neighborhood characteristics and spatially lagged terms, nonrandom (endogenous) neighborhood selection is a serious problem that might bias the estimates (Legewie 2012; Morgan and Winship 2014). Similar to research on neighborhood effects, residents might select into or out of neighborhood boundaries by moving to specific areas even conditional on the covariates, thereby biasing the estimates. In this sense, the analysis should be understood as a first step to establish the importance of boundaries. It reveals a consistent association between boundaries and crime but does not conclusively affirm the causal nature of this association.

Supplementary Analysis Based on Alternative Dependent Variables

Police-reported crime data can be problematic and do not capture all crimes (Lynch and Addington 2006). This concern is particularly acute because previous research has documented a relationship between neighborhood boundaries (the key independent variable) and the reporting of nuisances through nonemergency hotlines (Legewie and Schaeffer 2016). However, Part I violent crimes are serious offenses that tend to be reported more reliably than non-emergency nuisances. Nonetheless, I use two alternative measures of crime that allow me to replicate the analysis based on different crime measures and slightly different modeling strategies (see the next section for a description of the variables). The first is a measure of the number of homicides in each census

block in 2011. Compared with Part I index crimes, such as assault, data on homicides are more reliable and unlikely to be affected by underreporting. Similar to the main analysis, the number of homicides is a count variable, so the estimation strategy is the same for the two outcome variables. The second is a survey-based measure of perceived violence from the Chicago Community Adult Health Study (CCAH) (House et al. 2012). The CCAHS is a cross-sectional survey based on face-to-face interviews with 3,105 adult respondents in Chicago between 2001 and 2003. It provides information on the census block for each respondent and the level of violence they perceive. This survey-based measure of local crime is unaffected by biased police data and therefore addresses concerns about underreporting of Part I violent crimes. In contrast to the number of violent crimes, the measure of perceived violence is continuous and on the individual level. To model perceived violence, I use a linear regression with clustered standard errors. Formally, the model can be defined as

$$y_{ijg} = \alpha + \delta D_{jg} + \mathbf{X}_{jg}\boldsymbol{\beta}_1 + \mathbf{U}_g\boldsymbol{\beta}_2 + \mathbf{U}_{ijg}\boldsymbol{\beta}_3 + \varepsilon_{ijg},$$

where i, j, and g are indices for individuals, census blocks, and block groups, respectively. Similar to the main analysis, the term δD_{jg} refers to the measure of social neighborhood boundaries and estimates the relationship between neighborhood boundaries and perceived violence. In addition to the control variables on the block $\mathbf{X}_{jg}$ and block group level $\mathbf{U}_g$, the model includes a set of individual level covariates $\mathbf{U}_{ijg}$ with a corresponding vector of coefficients $\boldsymbol{\beta}_3$. In contrast to the main analysis, the census-based covariates are based on Summary File I and III from the 2000 decennial census. Thus, the analysis models perceived violence in 2001–2003 as a function of area characteristics from 2000. The two additional dependent variables and data sources allow me to examine the consistency of the results across different measures of crime.

Coding of Variables

Dependent Variables

The main dependent variable is the number of violent crimes per Chicago census block in 2011. The definition of violent crimes is based on the Uniform Crime Reports (UCR) Part I. Violent crimes include murder, manslaughter, forcible rape, robbery, and aggravated assault. The number of crimes per census block is aggregated from incident-level crime data from the Chicago Police Department. Violent crime is a relatively rare event, particularly when aggregated to small areal units, such as census blocks or block groups. As a result, the number or rate of crimes can be unstable. To alleviate this concern, I present sensitivity analyses that aggregate violent crime over a six-year period (2011–2016). For the second dependent variable used as part of the supplementary analysis, I restrict my crime measure to the number of homicides per census block in 2011 reported by the Chicago Police Department. The third dependent variable uses a survey-based measure of perceived violence from the 2001–2003 CCAH (House et al. 2012). The measure is based on a scale constructed from five items that asked respondents how often each of five incidents occurred in their neighborhood over the past six months: a fight involving a weapon, a violent argument

between neighbors, a gang fight, a sexual assault or rape, and a robbery or mugging (see House et al. 2012 for more details on the index).

Measuring Neighborhood Boundaries

The main independent variable is based on racial neighborhood boundaries at the census block level. Researchers from various disciplines have developed methods to detect neighborhood boundaries (Dale and Fortin 2014; Jacquez et al. 2000; Logan et al. 2011; Spielman and Logan 2013). These methods are often called "wombling" based on foundational work by Womble (1951). In ecology, they are used to identify boundaries (also called "ecotones") in species or habitat distributions, to study environmental factors associated with these boundaries, and to examine the effect of boundaries (Fagan et al. 2003). In computer vision, image processing, and machine learning, edge-detection algorithms are essential tools with applications ranging from image sharpening to robotics and driverless cars (Shapiro and Stockman 2001). A separate literature has focused on identifying neighborhoods and their boundaries based on complete-count microdata from historical censuses (Logan et al. 2011; Spielman and Logan 2013).

Most existing boundary analysis methods are designed for point-level (or raster-level) data. *Point-specific data* consist of points with known coordinates (latitude and longitude), such as incident-level crime data with precise information on the location of the crime. Neighborhood research based on contemporary data, however, generally relies on aggregated census data for geographical regions, such as census blocks, tracts, counties, or zip codes. *Areal data* refer to aggregated information for some region (e.g., census tracts, counties, or zip codes) with information on the location and shape of these regions (spatial polygons often in the form of shapefiles). Examples include the number of crimes per census tract in a certain time interval, or the racial composition and poverty rate across census tracts in the United States.

This article uses areal wombling as a boundary detection approach designed for areal data (Liang et al. 2009; Lu and Carlin 2005; Lu et al. 2007). It is based on the idea that two adjacent areas are separated by a boundary if the difference between the two areas in some response variable exceeds a threshold. The difference between all pairs of adjacent areas is estimated based on a distance metric, such as Euclidean distance, squared Euclidean distance, or Manhattan distance. More formally, consider an areal map, such as the one shown in the left side of Fig. 1, with $i = 1, \ldots, N$ regions, a response variable Y_i (e.g., proportion of African American residents, poverty rate, or number of violent crimes), and an adjacency matrix $\mathbf{A}$ that is defined as $a_{ij} = 1$ when i and j are adjacent and 0 otherwise. For each pair of adjacent regions, the *boundary likelihood value* (BLV) or the *boundary value* is defined as $D_{ij} = \|Y_i - Y_j\|$ where $\|\cdot\|$ is a distance metric. High boundary values reflect a large difference in the response variable between adjacent areas, indicating that the transition from i to j is part of the boundary. Figure 1 illustrates the result. It shows the proportion of African American residents across census tracts in Chicago on the left and the corresponding boundary values in the middle. Thicker lines indicate larger boundary values, which range from 0 (no difference in the proportion of African American

residents between two adjacent areas) to 1 (very large difference between adjacent areas).[3]

The boundary likelihood value or boundary value is based on a single response variable (e.g., proportion African American) and refers to a pair of adjacent regions represented by the borderline segment between the two areas. Census data, however, are available for areal units (census blocks, block groups, or tracts). To address this problem, I define the boundary value for an areal unit as the maximum boundary value between the focal areal unit and its neighbors. The right side in Fig. 1 illustrates the result. It shows the boundary value for the percentage African American across areal units in Chicago.

The analysis relies on three distinct measures based on these race-specific boundary values for areal units. First, I use the race-specific boundary values directly (e.g., for the correlation matrix in Table 1). Second, the main independent variable is a composite measure "neighborhood boundary" for multigroup settings. The composite measure combines the boundary values across different racial groups. This measure is defined as the maximum boundary value for a specific areal unit across the different race-specific values for proportion white, African American, Hispanic, and Asian. Finally, the supplementary analyses present results for different pairwise boundaries (white–African American, white-Hispanic, and African American–Hispanic boundaries). These pairwise boundaries are defined as the product of the two race-specific boundary values.

Control Variables

The models include a large set of control variables that condition on important neighborhood characteristics (for a full variable list, see Table A1 in the online appendix). The measures are common predictors in the literature on neighborhoods and crime (e.g., Kim and Hipp 2017; Morenoff et al. 2001). They adjust for internal neighborhood properties, common measures of spatial interdependence, and physical boundaries.

First, the models control for population size in 100s so that the results refer to the number of crimes relative to the number of residents in a census block. In supplementary analysis, I include population size as an offset so that the models focus on the per capita crime rate (Osgood 2000).

Second, I control for prior crime using violent and property crimes in 2001 (10 years prior to the outcome variable). Prior crime as a previous measure of the outcome variable is an important covariate in observational studies. It adjusts for many confounding factors and significantly reduces confounding bias (Shadish et al. 2008). The long temporal lag allows for changes in neighborhood boundaries over a 10-year period. However, a possible concern is that neighborhood boundaries are relatively stable even over this period. To address this concern, I examine the sensitivity of the results to various specifications of prior crime. These specifications include crime measures based on different years (2001, 2006, and 2010), crime measures for multiple

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[3] The correlation between boundary values based on Wombling and edge intensity as an alternative boundary detection method used by Legewie and Schaeffer (2016) ranges from 0.71 for proportion Hispanic to 0.74 for proportion African American.
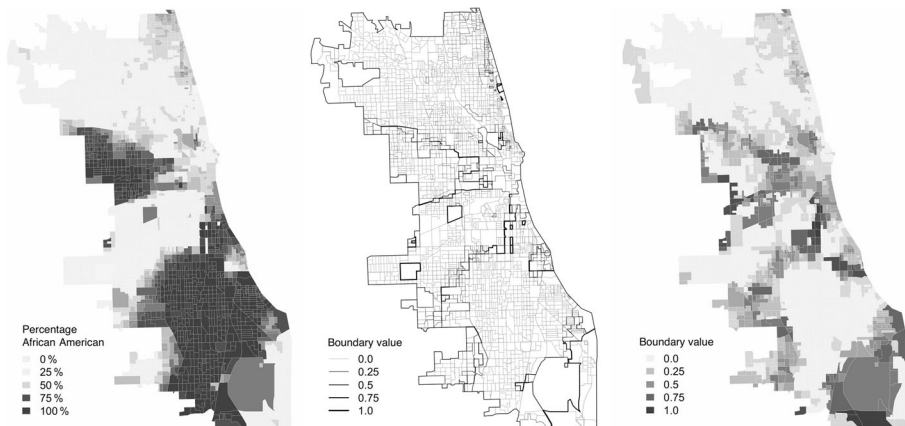
Fig. 1 Areal wombling for the proportion of African American residents in Chicago, 2010

years, and omitting prior crime entirely. The results are consistent with the findings presented here.

Third, I control for the racial composition of census blocks by including the proportion of African American, Hispanic, and Asian residents (with proportion white as the reference category), and a measure for racial/ethnic diversity based on the Hirschman-Herfindahl Index (HHI) (Hirschman 1964).[4] Controlling for racial composition and diversity is important because the focal independent variable is based on changes in the racial/ethnic composition across space. The variables ensure that the relationship between boundaries and crime is independent of internal neighborhood properties related to the racial composition of areas.

Fourth, I control for the proportion of men aged 15–35 as the "crime-prone population" on the census block level.

Fifth, the models include three structural neighborhood characteristics on the census block group level that are central in research on social disorganization theory and crime (e.g., Sampson et al. 1997): concentrated disadvantage, residential instability, and immigrant concentration. Following previous research (Sampson et al. 1997), all three are indexed control variables based on the predicted factor scores from an exploratory maximum likelihood factor analysis. The specific items, their factor loadings, and the eigenvalues are reported in Table A1 in the online appendix. The eigenvalues suggest one prominent factor for each of the three separate factor analyses. These factors can be interpreted meaningfully following previous research (Sampson et al. 1997). The variables adjust for the most common internal neighborhood properties in research on crime but are also limited by the fact that they are measured on a higher geographical level than the outcome variable.

Sixth, the analysis includes several control variables for physical and administrative boundaries. In particular, I include measures for major roads,[5] rivers, parks, and the

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[4] The definition of the index is $HH1 = 1 - \sum_{i=1}^{I} s_i^2$, where s is the population share of group i, and I is the number of groups in a given census block.

[5] Major roads are based on the 2010 TIGER/Line Files (U.S. Census Bureau 2012) and are defined as either divided, limited-access highways or main arteries that are part of the U.S. highway, state highway, or county highway system (primary or secondary roads).

Table 1 Summary statistics and correlation matrix for boundary values and common neighborhood measures (Chicago census blocks, 2010)

	Mean	SD	Area Characteristics			Spatial Lags			Neighborhood Boundary		
			1	2	3	4	5	6	7	8	9
1. Proportion White	0.30	0.34									
2. Proportion African American	0.38	0.44	−0.67***								
3. Proportion Hispanic	0.26	0.32	−0.19***	−0.56***							
4. Proportion White (spatial lag)	0.26	0.23	0.85***	−0.69***	−0.03***						
5. Proportion African American (spatial lag)	0.30	0.29	−0.68***	0.91***	−0.44***	−0.78***					
6. Proportion Hispanic (spatial lag)	0.22	0.17	−0.03***	−0.56***	0.82***	0.03***	−0.56***				
7. Boundary, White	0.20	0.20	0.46***	−0.53***	0.15***	0.49***	−0.55***	0.21***			
8. Boundary, African American	0.13	0.18	−0.18***	0.15***	−0.02***	−0.18***	0.15***	−0.05***	0.16***		
9. Boundary, Hispanic	0.21	0.20	0.17***	−0.42***	0.37***	0.24***	−0.43***	0.41***	0.56***	0.30***	
10. Boundary, Combined	0.28	0.23	0.22***	−0.37***	0.19***	0.27***	−0.38***	0.23***	0.77***	0.59***	0.79***

Note: All continuous variables are standardized for the final analysis.

***$p < .001$

borders of Chicago elementary school districts. All four measures for physical and administrative boundaries are binary and defined as adjacency to major roads, rivers, parks, and school district borders. Controlling for other types of boundaries ensures that the analysis examines the role of social neighborhood boundaries conditional on the physical structure of the city in terms of major roads and rivers and administrative borders, such as school districts.

Seventh, a growing literature focuses on spatial interdependence and examines the influence of the broader spatial context. In my analysis, it is important to adjust for these factors and determine the role of neighborhood boundaries above and beyond common measures of spatial interdependence. In the sociological literature, spatial interdependence is commonly modeled through spatial lags (for an overview of alternative methods, see Anselin 2003; Dormann et al. 2007). The following analysis conditions on spatially lagged measures of key independent variables to capture the racial composition of surrounding areas. In particular, I include spatial lags for the proportion of African American, Hispanic, and Asian residents (excluding the proportion white as a reference category) as well as a spatial lag for the diversity index. Spatial lags are a simple extension of regression models with an explanatory variable that is defined as the distance-weighted average value of surrounding areas. Formally, the spatial lags can be expressed as $\rho \mathbf{WX}$; ρ is the estimate for the spatial parameter, and $\mathbf{W}$ is a weights matrix that describes the spatial relationship between each pair of neighborhoods. The matrix is typically specified as a binary adjacency matrix or based on the inverse distance between each pair of blocks. In both cases, the spatial lags capture the average racial composition of surrounding areas. The analysis use the inverse distance between blocks for all blocks within 2 km, but the results are consistent across various definitions of the spatial weight matrix.

However, spatial lags introduce substantial multicollinearity problems. The variance inflation factor (VIF) is a measure to quantify the severity of multicollinearity. Without spatially lagged terms, the VIF is below the commonly used thresholds of 5 for all variables (Models 1–3 in upcoming Table 2). After adding spatial lags to the regression model, however, the factor increases for several variables. In particular, the spatial lags for proportion African American and Hispanic, and the diversity index are all above 5 and are as high as 11 for one of the variables. Omitting these variables does not change the results. Accordingly, the results for spatial lags should be interpreted with caution.

The covariates follow a clear temporal order. I predict the 2011 crime rate on the census block level as a function of the prior crime rate in 2001 and neighborhood characteristics (including neighborhood boundaries) measured with data from the 2010 census and the 2007–2011 five-year estimates from the ACS. I standardize all continuous variables with the exception of population size and the number of prior violent crimes.

Propagating Uncertainty From ACS Estimates

The margin of error (MOE) in ACS estimates for small geographical units, such as census block group, is generally large (Spielman et al. 2014). To address this problem, I propagate uncertainty from the ACS estimates to the final model estimates presented in the Results section using three steps. First, I use the MOE from the ACS to create 10 plausible values for each variable on the census block group level based on their

Table 2 Neighborhood boundaries and violent crime

	Model 1	Model 2	Model 3	Model 4
Population (in 100s)	0.056*	0.066**	0.066**	0.067**
	(0.024)	(0.023)	(0.023)	(0.023)
Violent Crime, 2001	0.238***	0.235***	0.222***	0.223***
	(0.011)	(0.011)	(0.010)	(0.010)
Property Crime, 2001	0.047***	0.046***	0.042***	0.043***
	(0.002)	(0.001)	(0.001)	(0.002)
Proportion African American	0.378***	0.400***	0.402***	0.335***
	(0.040)	(0.039)	(0.039)	(0.051)
Proportion Hispanic	0.221***	0.223***	0.221***	0.149***
	(0.029)	(0.028)	(0.028)	(0.034)
Proportion Asian	0.051**	0.046*	0.049*	0.027
	(0.020)	(0.019)	(0.020)	(0.023)
Concentrated Disadvantage	0.190***	0.188***	0.182***	0.170***
	0.029)	(0.028)	(0.028)	(0.028)
Residential Instability	0.041	0.040	0.040	0.039
	(0.160)	(0.157)	(0.156)	(0.158)
Immigrant Concentration	0.021	0.021	0.021	0.015
	(0.024)	(0.023)	(0.024)	(0.024)
Ethnic Diversity (HHI)	0.028	0.006	0.009	0.012
	(0.021)	(0.021)	(0.021)	(0.020)
Crime-Prone Population	0.136***	0.139***	0.140***	0.147***
	(0.020)	(0.019)	(0.019)	(0.020)
Racial Neighborhood Boundary		0.077***	0.069***	0.071***
		(0.016)	(0.016)	(0.017)
Major Road			0.313***	0.315***
			(0.071)	(0.071)
Adjacent to Park			−0.052	−0.049
			(0.054)	(0.054)
River			0.224	0.199
			(0.288)	(0.282)
Elementary School District Border			0.265***	0.262***
			(0.031)	(0.031)
Spatial Lag: Proportion African American				0.118
				(0.063)
Spatial Lag: Proportion Hispanic				0.105*
				(0.041)
Spatial Lag: Proportion Asian				0.054
				(0.031)
Spatial Lag: Ethnic diversity (HHI)				−0.016
				(0.044)
Constant	−1.865***	−1.870***	−1.940***	−1.945***
	(0.027)	(0.027)	(0.028)	(0.029)

Note: $N = 36{,}519$. Estimates are based on negative binomial regressions with clustered standard errors on the census block group level. Standard errors are shown in parentheses.

*$p < .05$; **$p < .01$; ***$p < .001$

sampling distribution. The plausible values are defined as random draws from a normal distribution, with the mean given by the ACS estimates and the standard deviation given by the standard error of the ACS estimates. Second, I calculate any derived variables based on each set of 10 plausible values. For example, the control variable "concentrated disadvantage" is based on the predicted factor scores from a factor analysis that combines five separate variables. To obtain plausible values for "concentrated disadvantage" that reflect the uncertainty in the census block group ACS estimates, I first obtain the plausible value for the five underlying variables and then recalculate the factor scores based on each set of plausible values. Finally, in the third step, I propagate the error from the ACS estimates by repeating the analysis for each set of plausible values. I then combine the results using Rubin's (2004) repeated imputation summary statistics. These estimates account for the uncertainty in the ACS estimates (Blackwell et al. 2017).

Empirical Results

My analysis begins with a simple correlation matrix presented in Table 1. The table shows the relationship between the racial/ethnic composition of Chicago census blocks as an internal characteristic of areas, spatially lagged terms that capture the racial composition of surrounding areas, and neighborhood boundaries as the focus of this article. The results indicate a partly close relationship between internal area characteristics and the corresponding spatially lagged terms. This close relationship with correlation coefficients as high as .85 for whites, .91 for African Americans, and .82 for Hispanics is a consequence of the high level of residential segregation in Chicago. Areas that are mainly African American tend to be surrounded by areas with similar racial composition. Social neighborhood boundaries, however, are empirically distinct. Indeed, the highest correlation between the combined measure for neighborhood boundaries and the spatially lagged terms is modest, at –.38.

Table A2 in the online appendix further explores the relationship between social neighborhood boundaries; physical boundaries in terms of major roads, rivers, and parks; and administrative boundaries in terms of elementary school district borders. The correlations are all positive but small (generally below .1), indicating that social, physical, and administrative boundaries are analytically distinct.

I continue by examining the relationship between neighborhood boundaries and crime. Table 2 presents the results from a series of negative binomial regression models. These models predict the number of violent crimes on the census block level as a function of internal neighborhood characteristics, spatially lagged terms, physical boundaries, and the measure of social neighborhood boundaries. Model 1 begins with internal area characteristics that are common in research on crime rates. It shows that the estimate for concentrated disadvantage is highly significant and substantial. The estimates for residential instability and immigrant concentration, however, are small and statistically insignificant. These findings confirm earlier research describing concentrated disadvantage as one of the most important neighborhood characteristics for the concentration of crime. Similarly, the racial composition of areas is related to crime, with large and highly significant estimates for the proportion of African American and Hispanic residents.

In Model 2, I add the measure for racial neighborhood boundaries as the focal independent variable. The findings indicate that the number of violent crimes is substantially higher at neighborhood boundaries conditional on internal properties of neighborhoods. The size of the coefficient is large and statistically significant. In particular, a 1 standard deviation difference in the composite measure for neighborhood boundaries corresponds to 8.0 % higher number of violent crimes. Model 3 adds control variables for physical and administrative boundaries. The results indicate that crime is higher at physical and administrative boundaries, replicating the results from previous research (Kim and Hipp 2017). More importantly, Model 3 shows that social neighborhood boundaries are related to crime conditional on other types of boundaries.

Finally, Model 4 extends the regression with a set of four spatially lagged measures of key independent variables to capture the racial composition of the broader spatial surrounding. The results show that the coefficient for social neighborhood boundaries remains large and statistically significant, indicating that the effect of neighborhood boundaries is substantial above and beyond internal properties of neighborhoods, other types of boundaries, and spatially lagged terms. The results also show that proximity to predominantly African American and Hispanic areas is related to higher crime rates conditional on the racial composition of the areas themselves. This finding is in line with a growing literature focused on spatial interdependence and highlights that the larger spatial surrounding is important in addition to the focal area itself. However, these results should be interpreted with caution because the correlation between the proportion of African American and Hispanic residents and the corresponding spatial lags is high, raising concerns about multicollinearity (see variables section for details).

Table 3 displays results of a number of supplementary analyses that confirm and extend the main finding. The analyses build on Model 4 in Table 2. The first column reports the results from a negative binomial regression, with population size as an offset or exposure variable and rate instead of number of crimes as a control variable. Offset or exposure variables transform count models of crimes to a model of per capita rates (Osgood 2000). The results are consistent across the different specifications of the population term and therefore both for models focused on the number of crimes and those focused on the rate of violent crime. Models 2 and 3 show the results separately for daytime and nighttime crime. The daytime and nighttime composition of areas varies substantially because many people work and live in different types of places (Ellis et al. 2004). These different compositional properties have potential implications for crime and neighborhood boundaries. The results show that the estimated coefficient for racial neighborhood boundaries is positive and statistically significant in both cases, but the effect is substantially larger for nighttime crime. Model 4 uses a measure for violent crime based on multiple years of data (2011–2016) as the outcome variable. This measure alleviates concerns that violent crime is a relatively rare event, particularly when aggregated to small areal units, and is therefore unstable. The results confirm the previous findings and show a positive and statistically significant relationship between neighborhood boundaries and violent crime. Finally, Model 5 presents the results for a different set of boundary measures. Instead of a composite measure, the model includes separate variables for white–African American, white-Hispanic, and African American–Hispanic boundaries. The results indicate that the relationship between neighborhood boundaries and crime is largely based on areas that transition from predominantly white to African American neighborhoods. In contrast, there is no

Table 3 Supplementary analysis: Neighborhood boundaries and violent crime

	Model 1	Model 2	Model 3	Model 4	Model 5
Population (in 100s)		0.154***	0.038	0.068**	0.061**
		(0.028)	(0.026)	(0.021)	(0.024)
Violent Crime, 2001	2.554***	0.206***	0.234***	0.221***	0.224***
	(0.061)	(0.012)	(0.012)	(0.008)	(0.010)
Property Crime, 2001	0.506***	0.032***	0.035***	0.061***	0.042***
	(0.009)	(0.001)	(0.002)	(0.002)	(0.001)
Proportion African American	0.330***	0.377***	0.291***	0.305***	0.305***
	(0.057)	(0.068)	(0.060)	(0.037)	(0.049)
Proportion Hispanic	0.070	0.160***	0.140***	0.111***	0.145***
	(0.041)	(0.044)	(0.042)	(0.024)	(0.034)
Proportion Asian	0.043	0.037	0.023	0.063***	0.036
	(0.028)	(0.031)	(0.028)	(0.016)	(0.023)
Concentrated Disadvantage	0.153***	0.165***	0.172***	0.197***	0.170***
	(0.030)	(0.037)	(0.029)	(0.024)	(0.028)
Residential Instability	0.061	0.039	0.041	0.047	0.040
	(0.185)	(0.145)	(0.172)	(0.164)	(0.157)
Immigrant Concentration	0.007	0.016	0.014	0.014	0.014
	(0.026)	(0.033)	(0.025)	(0.017)	(0.024)
Ethnic Diversity (HHI)	−0.061*	0.012	0.016	−0.001	0.011
	(0.024)	(0.028)	(0.025)	(0.014)	(0.021)
Crime-Prone Population	−0.108***	0.054**	0.166***	0.182***	0.146***
	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)
Racial Boundary	0.216***	0.105***	0.044*	0.054***	
	(0.017)	(0.021)	(0.020)	(0.012)	
Boundary: White–African American					0.074***
					(0.014)
Boundary: White-Hispanic					−0.004
					(0.018)
Boundary: African American–Hispanic					0.033**
					(0.012)
Major Road	0.614***	0.407***	0.243**	0.375***	0.324***
	(0.081)	(0.090)	(0.090)	(0.054)	(0.071)
Adjacent to Park	−0.132*	−0.042	−0.074	−0.020	−0.052
	(0.055)	(0.068)	(0.068)	(0.039)	(0.054)
River	0.257	0.228	0.117	0.052	0.148
	(0.402)	(0.284)	(0.340)	(0.203)	(0.292)
School District Border	0.361***	0.266***	0.274***	0.295***	0.262***
	(0.035)	(0.040)	(0.038)	(0.023)	(0.031)
Spatial Lags	Yes	Yes	Yes	Yes	Yes
Constant	−1.169***	−2.812***	−2.452***	−0.453***	−1.941***
	(0.023)	(0.035)	(0.034)	(0.024)	(0.029)

Notes: $N = 36{,}519$; Estimates are based on negative binomial regressions with clustered standard errors on the census block group level. The 2001 violent crime measure is coded as crime rates in Model 1 and as the number of crimes in the other models. Standard errors are shown in parentheses.

*$p < .05$; **$p < .01$; ***$p < .001$

evidence for an increased level of crime at white-Hispanic boundaries and a statistically significant but substantially small relationship between African American–Hispanic boundaries and violent crime.

The findings indicate that neighborhood boundaries are related to violent crime above and beyond internal characteristics of areas and other spatial processes. The data, however, fail to capture all crimes. To address this problem, I use two alternative data sources that allow me to reaffirm the findings based on different crime measures. The results are presented in Table 4, which compares the previous result for violent crimes (Model 1) with homicides (Model 2) and perceived violence (Model 3). These three dependent variables are based on different units of analysis (census blocks in Models 1 and 2 vs. individual survey respondents in Model 3) and use different estimation strategies (negative binomial regression in Models 1 and 2 vs. linear regression in Model 3), making it difficult to compare the size of the coefficient estimates directly. Nonetheless, the findings reaffirm the relationship between neighborhood boundaries and crime: both homicides and respondents' reports of perceived violence are higher in areas with high boundary values above and beyond internal neighborhood characteristics, spatially lagged terms for the racial composition, and individual attributes. However, the coefficient estimate for homicides is not statistically significant at the .05 level but is similar in size to the estimate for violent crime.

Conclusion

The concepts of the "edge" in Eastern City (Anderson 1990) and the "dividing line" in Chicago's South Side (Pattillo 2007) illustrate that social neighborhood boundaries are important for spatial demography and population research. These boundaries are meaningful and often contested separations of space into distinct areas. Although segregation has been a central topic in the study of spatial population dynamics, previous research has largely ignored that segregation creates areas of transition between relative homogeneous zones. The focus on neighborhood boundaries advances

Table 4 Neighborhood boundaries and various crime measures

	Model 1 (violent crime)	Model 2 (homicides)	Model 3 (perceived violence)
Racial Neighborhood Boundary	0.071***	0.097	0.039*
	(0.017)	(0.071)	(0.019)
Neighborhood Characteristics	Yes	Yes	Yes
Physical and Administrative Boundaries	Yes	Yes	
Spatial Lags	Yes	Yes	Yes
Individual Controls			Yes
Number of Observations	36,519	36,519	2,961
Level of Analysis	Census blocks	Census blocks	Individuals in census blocks

Note: Standard errors are shown in parentheses.

*p < .05; ***p < .001

spatial thinking in population science. Despite a renewed interest in spatial dimensions of social inequality, most research has analyzed neighborhoods as independent units without considering the broader sociospatial structure. Although this work continues to be essential for the progress of research on neighborhood inequality, this aspatial perspective to spatial population research contradicts many theoretical arguments about the spatial dimension of social inequality and stratification. A growing literature has addressed this problem in examining spatial dependence and proximity as key components of spatial inequality (Downey 2006; Sampson et al. 1999; Sharkey 2014; Law and Legewie forthcoming). This article contributes to this agenda by considering social neighborhood boundaries as a salient feature of the spatial structure. It elaborates the particular challenges and processes that occur at social neighborhood boundaries, argues that boundaries are related to various outcomes, and examines the relationship between racial neighborhood boundaries and violent crime as a key dimension of spatial inequality. In contrast to previous work on spatial interdependence, the focus on neighborhood boundaries highlights features of the sociospatial structure defined by a particular configuration of groups in space and not simply the proximity to differently composed areas. It adds a further element to spatial population research focused on where populations border and how sharp these borders are. Future research should extend this work by focusing on other social neighborhood boundaries, such as socioeconomic or partisan (Republican-Democratic) boundaries, and by examining the mechanisms that explain the relationship between boundaries and crime.

To my knowledge, the empirical results presented in this article provide the first systematic evidence for the relationship between neighborhood boundaries and violent crime. They show that the number of violent crimes is higher at neighborhood boundaries above and beyond internal neighborhood characteristics; spatially lagged terms as common measures of spatial interdependence; and other types of boundaries, such as major roads, rivers, or school district borders. This finding is consistent across three different measures of crime based on police-reported data, homicides, and survey-reported perceived violence. The analysis adjusts for internal neighborhood characteristics and spatially lagged terms as the most common measure of spatial interdependence. Nonetheless, the findings are limited by the observational nature of data, which makes it difficult to establish causality (Morgan and Winship 2014). Future work should examine the extent to which the estimates presented here are causal.

Aside from advancing neighborhood boundaries as an important concept in the neighborhood literature, this article introduces wombling as a boundary detection method to social scientists. In ecology, wombling is used to identify boundaries (ecotones) in species or habitat distributions, study environmental factors associated with these boundaries, and examine the effect of boundaries (Fagan et al. 2003). The method makes it possible to empirically determine boundaries between neighborhoods and track their change over time. It focuses on social neighborhood boundaries based on changes in the composition of neighborhoods across space, capturing the transition from a low-class to a high-class neighborhood or from a predominantly white to a predominantly Hispanic area. In contrast, symbolic neighborhood boundaries are conceptual categorizations of space into distinct areas, and political boundaries are administrative borders that divide geographical areas into school districts, police precincts, congressional districts, or others. Social neighborhood boundaries interact with symbolic and political boundaries in important ways.

   Social neighborhood boundaries defined by changes in the composition of neighborhoods across space are a common feature of highly segregated urban areas in the United States. Although traditional African American–white segregation is increasingly replaced by more complex patterns with multiple groups, racial and socioeconomic segregation remains a defining feature of urban life in the United States and in many countries across the world (Charles 2003; Johnston et al. 2007). A high level of segregation entails social neighborhood boundaries at places where neighborhoods transition from high to low poverty or from prominently white to prominently Hispanic. Although previous research has acknowledged the importance of these boundaries, few studies have considered and systematically examined the relationship between boundaries and other phenomenon. The importance of neighborhood boundaries documented in this article demonstrates the need for a more refined approach to the study of place and space in sociological research and proposes corresponding methods to achieve this goal. Future research should consider the role of spatial features, such as boundaries or enclaves embedded in differently composed larger communities, to advance spatial thinking in the social sciences.

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