

# 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 inter-group 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.

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In 1945, St. Clair Drake and Horace R. Cayton's *Black Metropolis* (1993, p. 190) argued 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, p. 154-56) reported about "the edge" in Eastern City as "the place where two communities meet, where the lower-income black residents come in contact with the middle- and upper-income white ones" (Anderson 1990, p. 154). Pattillo (2007) describes 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, analyzes neighborhoods as independent units without considering the broader socio-spatial structure. A rapidly growing literature addresses this problem and moves beyond the treatment of neighborhoods as isolated islands.<sup>1</sup> This work considers proximity and dependencies between geographic areas as a key component of spatial inequality (Morenoff & Sampson 1997; Sampson, Morenoff, & Earls n.d.; 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, this article argues that these boundaries are an important aspect of the socio-spatial structure with implications for crime and a range of different outcomes.

For this end, this article first elaborates a theoretical argument about the particular challenges and processes that occur at social neighborhood boundaries. Just

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<sup>1</sup>Related research attempts to overcome the limitations of pre-defined, mutually exclusive spatial units with nonoverlapping boundaries and instead uses alternative definitions of neighborhoods (Sampson, Raudenbush, & Earls n.d.; Hipp et al. 2012; Spielman & Logan 2013).

as “the edge” in Eastern City and the “dividing line” in Chicago’s South Side, social boundaries capture the transition from a low 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 political boundaries defined as administrative borders that divide geographical areas into school districts, police precincts, congressional district 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 inter-group 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, this article presents 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 relation is consistent across different measures of crime including incident-level police data, geo-coded 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.

## **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 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 & Molnar 2002, 168). Just as “the edge” in Eastern City and the “dividing line” in Chicago’s South Side, these socially constructed neighborhoods are partly based on social boundaries but also influence the selection of residents into neighborhoods. Along similar lines, Campbell et al. (2009) use interviews with 37 adolescents and 33 parents to examine subjectively constructed neighborhood boundaries (see also Hwang 2015). They find that ethno-racial 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, 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 2015).

Building on the idea that the physical environment creates criminal opportunities, previous research has linked physical and administrative boundaries to criminal behavior (Kim & Hipp 2017; Brantingham et al. 2009; Song et al. 2017). Kim and Hipp (2017), for example, empirically test of this hypothesis. Using data from Southern California, they show that the level of crime is higher at physical (inter-state highways, parks and rivers) and city boundaries. Other work similarly finds

higher crime rates at spatial boundaries defined by changes in land use classification (Song et al. 2013, 2017). This research highlights the importance of physical and administrative boundaries for crime.

This article, in contrast, focuses on social boundaries based on the distribution of the population across neighborhoods. Social boundaries are defined by changes in the composition between adjacent areas. They can be sharp at points with abrupt compositional changes that clearly separate space into distinct areas, and they can be soft or fuzzy at points with extended zones of transition (K. Lynch 1960; Spielman & Logan 2013; Logan 2012; Legewie & Schaeffer 2016). Social neighborhood boundaries are closely linked to spatial segregation. They are located at the edges of highly segregated areas and a defining aspect of urban life in the United States and in many countries across the world (Roberto 2015). As such, they demarcate distinct areas and thereby create “organic” neighborhoods. Similar to physical barriers such as railways, major roads and rivers (Kim & Hipp 2017), Anderson’s and Pattillo’s ethnographic accounts suggest that boundaries have consequences for those residing nearby above and beyond demarcating distinct areas.<sup>2</sup> Other research provides further support. Desmond and Valdez (2012), for example, find 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 non-black residents who feel threatened by their black neighbors. Legewie and Schaeffer (2016) show that the number of complaints about neighbors making noise, blocking the driveway, or drinking in public is higher at boundaries between ethnically homogeneous neighborhoods. They explain this pattern with conflict between groups around contested boundaries.

There are at least two possible mechanism that explain why bordering regions at segregated locals are important for crime and possibly other outcomes. The first mechanism builds on social disorganization theory and the concept of collec-

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<sup>2</sup>Also note Pattillo’s later work (2013; 2005). In “Black Picket Fences”, she argues 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).

tive efficacy (Sampson & Groves 1989; Sampson, Raudenbush, & Earls n.d.; Sampson 2012). Similar to areas with residential instability or ethno-racial heterogeneity, neighborhood boundaries defined by transitions between differently composed homogeneous areas are characterized by lower level of informal social interactions, solidarity and trust that is 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 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 (1993 [1945], p. 190) describe these areas as a “racial no man’s land” without a cohesive neighborhood community that might be present in adjacent homogeneous areas. 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 increase the likelihood of crime.

Second, intergroup competition, group threat and defended neighborhoods theories might explain the relevance of boundaries for crime and other outcomes (Blumer 1958; Blalock 1967; 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 non-material issues such as the prevailing way of life or the use of public space (Legewie & Schaeffer 2016). This argument resonates with a number of ethnographic studies

from the *defended neighborhoods* perspective. Based on fieldwork observations in white urban 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 (Suttles 1972; Rieder 1985; DeSena 1990). Along these lines, Andrews and Seguin (2015) argue (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. An example of this process are the race riots of the early 20th century. Janowitz (1979, p. 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, p. 41) describe the 1992 Los Angeles riots in similar terms. They find increased violence in the “contact zone” or “contested area” located between the Latino and African American community (see also Grimshaw 1960). More recently, Legewie and Schaeffer (2016) assert that zones of transition between areas populated by different groups are particularly 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 provoking inter-group 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 geo-coded, 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 5-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 major metropolitan areas. In Chicago, there are 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, which are a common approach in research on crime (Osgood 2000). Negative binomial regressions are appropriate for count data confined to positive integers and allow for over-dispersion across census blocks (Gelman & Hill 2007, p. 115; Long & Freese 2005, Ch. 8). I use clustered standard errors to account for the clustering of census blocks in block groups (some control variables are measured



on the block group level) (Angrist & Pischke 2008, Ch. 8.2). Formally, the model can be defined as

$$\lambda_{jg} = \exp(\alpha + \delta D_{jg} + \mathbf{X}_{jg}\beta_1 + \mathbf{U}_g\beta_2)$$

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  $\delta$  estimates the relation 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  $\beta$ '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. While the analysis adjusts for internal neighborhood characteristics and spatially lagged terms, nonrandom (endogenous) neighborhood selection is still a problem that might bias the estimates (Morgan & Winship 2014; Legewie 2012). 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 and thereby bias 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 does not capture all crimes (J. P. Lynch & Addington 2006). This concern is particularly acute because previous research has docu-

mented a relation between neighborhood boundaries (the key independent variable) and the reporting of nuisances through non-emergency hot-lines (Legewie & Schaeffer 2016). However, Part I violent crimes are serious offenses that tend to be reported more reliably compared to 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 below for a description of the variables). The first is a measure of the number of homicides in each census block between 2011 and 2016. Compared to Part I index crimes such as assault, homicides are far more reliable and unlikely to be affected by underreporting. Similar to the main analysis, the number of homicides is a count variable so that 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 (CCAHS) from 2001 to 2003 (House et al. 2011). 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

$$y_{ijg} = \alpha + \delta D_{jg} + \mathbf{X}_{jg}\beta_1 + \mathbf{U}_g\beta_2 + \mathbf{U}_{ijg}\beta_3 + \epsilon_{ijg}$$

where  $i$ ,  $j$  and  $g$  are indices for individuals, census blocks and block groups respectively. Similar to the main analysis, the term  $\delta D_{jg}$  refers to the measure of social neighborhood boundaries and estimates the relation 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  $\beta_3$ . In contrast to the main

analysis, the census-based covariates are based on Summary File I and III from the 2000 Decennial Census so that 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 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 analysis 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 from 2011 to 2016 reported by the Chicago Police Department. The third dependent variable uses a survey-based measure of perceived violence from the Chicago Community Adult Health Study (CCAHS) from 2001 to 2003 (House et al. 2011). The measure is based on a scale constructed from five items that asked respondents how often certain incidents occurred in their neighborhood over the past 6 months. The incidents are 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. 2011 for more details on the index).

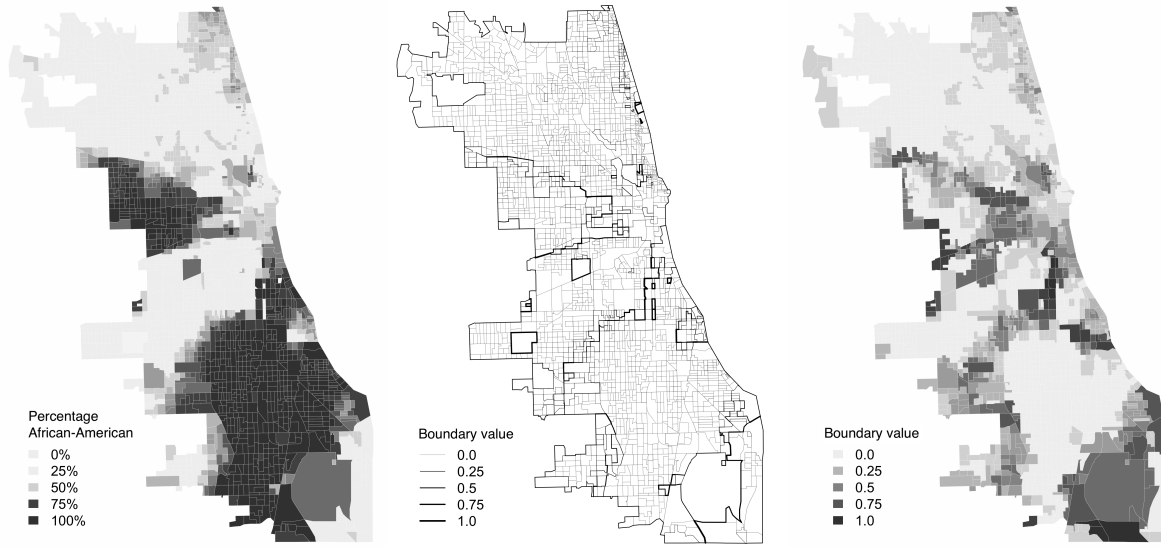
**Measuring neighborhood boundaries** The main independent variable is based on racial neighborhood boundaries on the census block level. Researchers from

various disciplines have developed methods to detect neighborhood boundaries (Dale & Fortin 2014; Jacquez et al. 2000; Logan et al. 2011; Spielman & 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, study environmental factors associated with these boundaries and examine the effect of boundaries (Fagan et al. 2003). In computer vision, image processing, and machine learning, edge detection algorithms are an essential tool with applications ranging from image sharpening, over robotics, to driver-less cars (Shapiro & Stockman 2001). A separate literature focuses on identifying neighborhoods and their boundaries based on complete-count micro-data from historical censuses (Logan et al. 2011; Spielman & Logan 2013).

Most existing boundary analysis methods are designed for point- (or raster-) level data. Point-specific data consists 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 refers 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 in a certain time-interval, the racial composition, or poverty rate across census tracts in the United States.

This article uses *areal wombling* as a boundary detection approach designed for areal data (Lu & Carlin 2005; Lu et al. 2007; Liang et al. 2009). 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 Figure 1 on the left with  $i = 1, \dots, N$  regions, a response variable  $Y_i$  (e.g., proportion of African-American

Figure 1: Areal wombling for the Proportion of African-American Residents in Chicago, 2010



residents, poverty rate or number of violent crimes), and an adjacency matrix  $A$  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 side and the corresponding boundary values in the middle. Thicker lines indicate larger boundary values. They range from 0 (no difference in the proportion of African-American residents between two adjacent areas) to 1 (very large difference between adjacent areas).<sup>3</sup>

The boundary likelihood value or boundary value is based on a single response variable (e.g. proportion African-American). It refers to a pair of adjacent regions represented by the border line segment between the two areas. Census data, how-

<sup>3</sup>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.

ever, is 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 hand side in Figure 1 illustrates the result. It shows the boundary value for the proportion 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 (for example, for the correlation matrix in Table 1). Second, the main independent variable is a composite measure “neighborhood boundary” for multi-group 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 pair-wise boundaries (white-black, white-Hispanic and black-Hispanic boundaries). These pair-wise 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). The measures are common predictors in the literature on neighborhoods and crime (e.g. Morenoff et al. 2001; Kim & Hipp 2017). 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 (ten 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 ten 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 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 black, 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).<sup>4</sup> Controlling for racial composition and diversity is important considering that the focal independent variable is based on changes in the racial and ethnic composition across space. The variables ensure that the relation 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 between 15 and 35 as the “crime-prone population” on the census block level.

Fifth, the models include structural neighborhood characteristics on the census block group level that are central in research on social disorganization theory and crime (e.g. Sampson, Raudenbush, & Earls n.d.). The characteristics are concentrated disadvantage, residential instability and immigrant concentration. Following previous research (Sampson, Raudenbush, & Earls n.d.), 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. The eigenvalues suggest one prominent factor for each of the three separate factor analyses. These factors can be interpreted

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<sup>4</sup>The definition of the index is  $HHI = 1 - \sum_{i=1}^I s_i^2$  where  $s$  is the population share of group  $i$  and  $I$  is the number of groups in a given census block.

meaningfully following previous research (Sampson, Raudenbush, & Earls n.d.). 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<sup>5</sup>, rivers, parks, and the 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 Dormann et al. 2007; Anselin 2003). The following analyses 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  $\rho WX$ .  $\rho$  is the estimate for the spatial parameter and  $W$  is a weights matrix that describes the spatial relation between each pair of neighborhoods. The matrix is typically spec-

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<sup>5</sup>Major roads are based on the 2010 TIGER/Line Files (Bureau 2012). They 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).



ified 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 below use the inverse-distance between blocks for all blocks within 4 kilometer 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, VIF is below the commonly used thresholds of 5 for all variables (Model I-III in Table 2 below). After adding spatial lags to the regression model, however, the factor increases for several variables. In particular, the spatial lags for African-American, 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 5-year estimates from the American Community Survey. 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 are 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. The propagation of uncertainty is based on three steps: First, I use the MOE from the American Community Survey to create 10 plausible values for each variable on the census block group level based on their 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 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, I propagate the error from the ACS estimates by repeating the analysis for each set of plausible values. The results are then combined 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 relation 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 relation between internal area characteristics and the corresponding spatially lagged terms. This close relation with correlation coefficients as high as 0.85 for White, 0.91 for Black and 0.82 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 with  $-0.38$ .

Appendix Table A2 further explores the relation 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 0.1) indicating that social, physical and administrative boundaries are analytically distinct. One of the reasons is that social neighborhood boundaries are not defined at rivers and parks. Elementary school district borders are sometimes aligned with social boundaries but more frequent and spread throughout Chicago even in predominantly white or African-American areas.

I continue by examining the relation 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 I begins with internal area characteristics that are common in research on crime rates. It shows that the estimate for concentrated disadvantage as the most prominent structural characteristics in the social disorganization literature is highly significant and substantial. The estimates for residential instability and immigrant concentration, however, are small and statistically insignificant. These findings confirm earlier research that describes 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 II, 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 one standard deviation difference in the composite measure for neighborhood boundaries corresponds to 8.0% higher number of violent crimes. Model III adds control variables for physical and administrative boundaries. The results indicate that crime is higher at physical and administrative boundaries replicating

Table 1: Summary Statistics and Correlation Matrix for Boundary Values and Common Neighborhood Measures (Chicago Census Blocks, 2010)

	Mean	SD	Area Characteristics			Spatial Lags			NBHD Boundary		
			1	2	3	4	5	6	7	8	9
1. Prop. White	0.30	0.34									
2. Prop. Black	0.38	0.44	-0.67***								
3. Prop. Hispanic	0.26	0.32	-0.19***	-0.56***							
4. Prop. White (spatial lag)	0.26	0.23	0.85***	-0.69***	-0.03***						
5. Prop. Black (spatial lag)	0.30	0.29	-0.68***	0.91***	-0.44***	-0.78***					
6. Prop. Hisp. (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 (Black)	0.13	0.18	-0.18***	0.15***	-0.02***	-0.18***	0.15***	-0.05***	0.16***		
9. Boundary (Hisp.)	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: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ; All continuous variables are standardized for the final analysis.

Table 2: Neighborhood Boundaries and Violent Crime

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

Note: N=36,519; Estimates based on negative binomial regressions with clustered standard errors on the census block group level.

$p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ; standard errors in parentheses

Table 3: Supplementary Analysis: Neighborhood Boundaries and Violent Crime

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

Note: N=36,519; Estimates 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 I and as the number of crimes in the other models.

$p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ; standard errors in parentheses

the results from previous research (Kim & Hipp 2017). More importantly, model III shows that social neighborhood boundaries are related to crime conditional on other types of boundaries.

Finally, model IV extends the regression with a set of four spatially lagged measures of key independent variable 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. It indicates 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. It highlights that the larger spatial surrounding is important in addition to the focal area itself. However, these results should be interpreted with caution considering that the correlation between the proportion of black and Hispanic residents and the corresponding spatial lags is high raising concerns about multicollinearity (see variables section for details).

Table 3 includes a number of supplementary analyses that confirm and extend the main finding. The analyses build on Model IV 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 control variables. 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 and the rate of violent crime. Model II and III 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 coef-

Table 4: Neighborhood Boundaries and Various Crime Measures

	Model I (Violent Crime)	Model II (Homicides)	Model III (Perceived Violence)
Racial Neighborhood Boundary	0.071*** (0.017)	0.097 (0.071)	0.039* (0.019)
Neighborhood Characteristics	✓	✓	✓
Physical and Admin. Boundaries	✓	✓	
Spatial Lags	✓	✓	✓
Individual Controls			✓
Observations	36,519	36,519	2,961
Level of Analysis	Census blocks	Census blocks	Individuals in census blocks

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ; standard errors in parenthesis.

ficient for racial neighborhood boundaries is positive and statistically significant in both cases but the effect is substantially larger for nighttime crime. Model IV 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 therefore unstable. The results confirm the previous findings and show a positive and statistically significant relation between neighborhood boundaries and violent crime. Finally, Model V presents the results for a different set of boundary measures. Instead of a composite measure, the model includes separate variables for white-black, white-Hispanic and black-Hispanic boundaries. The results indicate that the relation between neighborhood boundaries and crime is largely based on areas that transition from predominantly white to African-American neighborhoods. In contrast, there is no evidence for increased level of crime at white-Hispanic boundaries and a statistically significant but substantially small relation between black-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 al-



ternative data sources that allow me to reaffirm the findings based on different crime measures. The results are presented in Table 4. It compares the previous result for violent crime (Model I) with homicides (Model II) and perceived violence (Model III). Note that the three dependent variables are based on different units of analysis (census blocks in Model I and II versus individual survey respondents in Model III) and use different estimation strategies (negative binomial regression in Model I and II versus linear regression in Model III). These differences make 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 "edge" in Eastern City and the "dividing line" in Chicago's South Side 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. While segregation has been a central topic in the study of spatial population dynamics, previous research largely ignores that segregation creates areas of transition between relative homogeneous zones. The focus on neighborhood boundaries advances spatial thinking in population science. Despite a renewed interest in spatial dimensions of social inequality, most research analyzes neighborhoods as independent units without considering the broader socio-spatial structure. While 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 addresses this problem and examines spatial dependence and proximity as key components of spatial inequality (Downey 2006; Sampson, Morenoff, & Earls n.d.; Sharkey 2014; Law & Legewie 2018). This article contributes to this agenda. It considers social boundaries as a salient feature of the spatial structure, elaborates the particular challenges and processes that occur at social neighborhood boundaries, argues that boundaries are related to various outcomes, and examines the relation 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 socio-spatial 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 mechanism that explain the relation between boundaries and crime.

The empirical results provide the first systematic evidence for the relation between neighborhood boundaries and crime (for an exception see Legewie and Schaeffer 2016). 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 make it difficult to establish causality (Morgan & 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 scientist. In ecology, wombling is used to identify boundaries (also called 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. It captures the transition from a low to a high-class neighborhood or from a predominantly white to a 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 district 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. While traditional black-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 Hispanic. While previous research acknowledges the importance of these boundaries, few studies consider and systematically examine the relation 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 science.

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## Appendix A Supplementary Information

Table A1: Description of Variables

Variables	Description
<i>Dependent Variables</i>	
Violent Crime	Number of violent crimes in 2011 (UCR part I)
Homicides	Number of homicides between 2011 and 2016
Perceived Violence	Five-item index: fight with weapon, violent argument btw. neighbors, gang fight, sexual assault, and robbery or mugging.
<i>Independent Variables</i>	
NBHD Boundary: Race	Measure of ethno-racial neighborhood boundaries based on changes in the racial/ethnic composition across census blocks.
Population	Population in 100s (used as offset in sensitivity analysis)
Prior crime rate	Violent and property crime rate in 2001
Racial composition	Three separate variables for the proportion of African-American, Hispanic and Asian residents
Concentrated disadvantage	Five-item index based on factor analysis (eigenvalue 2.20, factor loadings in parenthesis): poverty rate (0.70), unemployment rate (0.67), professional and management jobs (-0.56), share of high-school graduates (0.47), share single mother families (0.86)
Residential instability	Three-item index based on factor analysis (eigenvalue 2.12, factor loadings in parenthesis): percentage of renter-occupied units (0.41), share of residents who moved to another dwelling since 2005 (0.31), housing unit rental vacancy rate (0.94)
Immigrant concentration	Three-item index based on factor analysis (eigenvalue 2.50, factor loadings in parenthesis): share of foreign born residents (0.92), share of residents who speak English less than “very well” (0.99), share of Spanish speaking residents (0.82)
Ethno-racial diversity	Hirschman-Herfindahl Index (HHI)
Crime-prone population	Share of 15 to 34 year old males
Physical Boundaries	Physical neighborhood boundaries measured with three indicator variables for adjacency to major road, park and river.
School District Border	Indicator variables for adjacency to the border of elementary school districts.
Spatially lagged terms	Spatially lagged terms for proportion of black, Hispanic and Asian citizens, and the diversity index
<i>Individual-Level Control Variables (CCAHS analysis only)</i>	
Gender	Dummy variable coded as 0 for men and 1 for women
Education	Education measured as years of education
Race/Ethnicity	Categorical variable coded as Non-Hispanic White (reference), Non-Hispanic Black, Asian, Hispanic, and Other
Age	Age in years
Home Ownership	Dummy variable indicating home ownership
Foreign born	Dummy variable for foreign born

Note: All continuous control variables are standardized.

Table A2: Summary Statistics and Correlation Matrix for Social, Physical and Administrative Boundaries (Chicago Census Blocks, 2010)

	Mean	SD	NBHD Boundary				Physical Boundary			
			1	2	3	4	5	6	7	
1. NBHD Boundary (White)	0.20	0.20								
2. NBHD Boundary (Black)	0.13	0.18	0.16***							
3. NBHD Boundary (Hispanic)	0.21	0.20	0.56***	0.30**						
4. NBHD Boundary (combined)	0.28	0.23	0.77***	0.59***	0.79***					
5. Adjacent to Major Road	0.03	0.18	0.09***	0.03***	0.07***	0.09***				
6. Adjacent to Park	0.07	0.25	0.02**	0.04***	-0.01	0.02***	0.04**			
7. Adjacent to River	0.00	0.04	0.05***	0.03***	0.02***	0.04***	0.03***	0.05***		
8. Elem. School District Border	0.26	0.44	-0.02***	0.04***	0.01*	0.00	0.05***	0.05***	0.04***	

Note: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ; All continuous variables are standardized for final analyses.