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**Both Sides of the Street: Introducing Measures of Physical and Social Boundaries Based on
Differences across Sides of the Street, and Consequences for Crime**

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Both Sides of the Street: Introducing Measures of Physical and Social Boundaries Based on Differences across Sides of the Street, and Consequences for Crime

Abstract

Objectives: Although previous studies have theorized the importance of physical and social boundaries (edges) in understanding crime in place, the relationship between edges and the level of crime has been less studied

empirically. The current study examines the effects of physical and social boundaries on crime in street segments.

Methods: To empirically measure boundaries, we introduce an approach of looking at the differences of land use (physical boundary), socioeconomic status, or racial composition (social boundaries) on both sides of a street segment. We estimated a series of negative binomial regression models in which measures of the physical and social boundaries are included while controlling for the effects of structural characteristic and the conventional physical boundary measures of highways, parks, and rivers.

Results: We observed that there are positive relationships between all three of these boundary measures and violent and property crimes. The results indicated that physical and social boundaries are important to consider in understanding the spatial patterns of crime. Moreover, the current study confirmed the moderating effects between social and physical boundaries.

Conclusions: Our results indicate that although much empirical research focuses solely on physical boundaries, our measures of social and physical boundaries have important consequences for the spatial location of crime, and therefore are worthy of further research.

Both Sides of the Street: Introducing Measures of Physical and Social Boundaries Based on Differences across Sides of the Street, and Consequences for Crime

Introduction

Scholars have theorized how spatial boundaries can be important for understanding the location of crime. Edges are the spatial boundaries where noticeable changes are observed (Brantingham & Brantingham, 1993). Edges can be physically pronounced or can be non-physically visible but socially recognized. Physical boundaries are defined as more visually pronounced boundaries. For example, various types of physical boundaries such as interstate highways, rivers or parks can serve as pronounced edges. Also, locations where different land use zones adjoin are seen to be edges. Indeed, empirical studies have tested whether places near physical boundaries actually have more crime than others (Brantingham and Brantingham 1975; Brantingham and Brantingham 1978; Brantingham et al. 2009; Song, Spicer, and Brantingham 2013; Song et al. 2015; Kim and Hipp 2017).

The other type of edge is non-physical, or a social boundary. Legewie (2018) defined social boundaries by abrupt changes in composition between adjacent areas that can separate space into two different sides. Although previous studies on edges have provided considerable insights for physical boundaries and crime in place, a limitation is that they often neglect the importance of social boundaries. To our knowledge, Legewie (2018) is the only study that explicitly theorized and empirically tested how social (racial) boundaries are associated with crime while accounting for the effects of other physical boundaries. He found that neighborhoods near racial boundaries are at higher risk of violent crime net of other neighborhood structural characteristics and physical boundaries such as major roads, rivers, or park boundaries.

Edges

In spite of the theoretical importance in understanding crime, relatively less attention has been paid to whether areas near physical and social boundaries actually have more or less crime. The current study examines the effects of physical and social boundaries on levels of crime within street segments. To empirically measure boundaries, we introduce a novel approach of looking at the differences of land use (physical boundary), socioeconomic status, or racial composition (social boundaries) on both sides of a street segment. Whereas street segments—both sides of a street between two intersections—are often conceived as appropriate social environments, we hypothesize that residents' perceptions of this environment can be negatively impacted if there are sharp physical or social differences between the two sides of the street. We therefore posit that a street segment has the ability to function as spatial boundary in instances in which it has dissimilar qualities of physical and social environmental features on each of the sides. By identifying physical and social characteristics of both sides of a street segment and calculating the difference between the two, our approach assesses whether these differences might help in conceptually capturing the locations of edges in terms of physical and social environmental features, as well as their possible impact on the spatial patterns of crime. In the subsequent sections, we discuss the theoretical motivations of the current study and explain why physical and social boundaries are important in understanding the spatial patterns of crime. Then we describe the methodological techniques employed in the current study to empirically test the association between various types of boundaries and crime in street segments.

Spatial Boundaries (Edges) and Crime

One possible theoretical framework to explain why spatial boundaries matter for understanding crime in place builds on social disorganization theory. The theory views that the

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absence or breakdown of informal social control is a key mediating component between social disorganization and crime (Sampson, Raudenbush, and Earls 1997; Sampson and Groves 1989; Kubrin and Weitzer 2003). Although studies of criminology of place have paid less attention to the importance of social disorganization theory, it is also applicable to understanding crime patterns at the micro scales such as street segments. Wicker (1987) views street segments as small scale social communities (behavior settings) where people constantly move in and out, get to know each other, and develop own social norms (Taylor 1997). Therefore, street segments “are microcommunities as well as microplaces”(Weisburd, White, and Wooditch 2020 p.4) that contain the structural characteristics of communities present in social disorganization theory. Therefore, “if the street segment can be seen as a type of ‘micro community,’ then social disorganization theory and the mechanism of informal social control or collective efficacy would seem to have (in)direct relevance to the understanding of the criminology of place (Weisburd, Groff, and Yang 2012, 2014; Weisburd et al. 2017). Indeed, some recent empirical studies confirmed that the mechanism of informal social control or collective efficacy can be an important factor that can determine the level of crime in small places. For instance, Weisburd, White, and Wooditch (2020) measured collective efficacy at the street segment level using survey data in Baltimore City, MD. They confirmed that collective efficacy at the street-segment level is strongly related to crime in place while accounting for various structural characteristics.

The hypothesized importance of boundaries is typically focused on how they can create breaks at a larger scale in the social landscape—that is, between street segments rather than upon them. For example, an important feature of spatial boundaries is their permeability – the level of accessibility of areas from the other side of the boundaries. Some areas near the boundaries are

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less accessible because of their physical characteristics. This may reduce the chance of social interactions among the residents living in the areas adjacent to them. For instance, rivers are particularly impermeable and crossing them requires additional cost, such as a bridge or ferry connection. So, crossing a river to get to the other side takes more time and effort; thus it impedes the chance of social interaction among residents living near the river in spite of their geographical proximity.

The accessibility of highways is another example. Highways can be physical barriers because crossing them typically requires over- or under-passes, although they are more permeable than rivers. Indeed, Hipp et al. (2014) referred to this idea as “social porosity” and found that the presence of physically visible boundaries (*wedges*) reduced the level of cohesion and informal social control in the neighborhoods adjacent to them because of lower level of accessibility. In a recent study Kim and Hipp (2017) empirically examined the associations between various types of physical boundaries (freeways, rivers, and park boundaries) and found that street segments near these boundaries are at higher risk of violent and property crime; and furthermore there is a distance decay effect as segments further away from physical boundaries tend to have lower risk of crime, in general.

In these examples, scholars typically focus on how boundaries between street segments can impact crime. However, given the theoretical applicability of social disorganization theory at the street segment level, herein we expand our understanding of spatial boundaries and crime patterns in street segments in the context of the informal social control thesis, and how it may operate *within* a street segment. An area containing a long stretch of an edge can be bisected into separate areas. In such areas, residents may have difficulty establishing social ties with those on the other side of the street, which decreases the level of neighboring, attachment, and

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cohesiveness. Therefore, areas near physical boundaries may have *higher* risk of crime due to a reduced number of social ties, sense of cohesion, and informal social control among the residents on one side of the boundary and the other.

The implication of this perspective is that there is something about the distinction between one side of the street and the other. This is distinct from simply considering whether there is more mixing on a street segment—whether based on land use, or various social characteristics—but that such differences become more pronounced in the minds of persons when they occur across the sides of a street. To some extent, this perceptual idea builds on the ideas of psychologists who have pointed out the ability of humans to create a sense of “groupness” based on quite trivial characteristics, or even in completely contrived settings (Tajfel 1981; Turner 1987; Tajfel and Turner 1986). Here, we posit that even though we agree with scholars who consider street segments to be social units in themselves (Taylor 1997), the distinction between the two sides of the street can nonetheless be salient to residents

Physical Boundaries

Brantingham and Brantingham (1993) note that because edges are where noticeable changes of physical environment are observed, they contain mixes of land uses and physical features that concentrate criminal opportunities and reduce surveillance by stable residents who are committed to keeping their community safe. Therefore, strangers can access edges more easily because the physical environment tends to promote more anonymity and less surveillance. These considerations suggest that land use compositions that can act as crime generators may also function as edges to shape human activity and thus facilitate crime patterns. Herein, we extend the idea of physical boundaries and argue that land use difference across the two sides of a street segment can operate as a type of physical boundary that impacts the perceptions of the

Edges

residents on that street. According to the Brantinghams (1993), there will be higher concentrations of crime along major sites of routine activities (nodes) and access routes (paths), and also more crime on the exterior boundaries of areas (edges) but less crime towards the interior of them. Peripheral areas have higher risk of crime than the interiors because residents tend to not consider the area as part of their own space; thus feel less responsible for surveillance. Although it is not easy to define where the peripheral areas exactly are, the current study utilizes a change in land use across the two sides of the street segment to identify the locations of outer areas.

In an empirical study of the Municipality of Burnaby in British Columbia, Canada, Song et al. (2013) defined edges as whenever another land use classification (Commercial, Residential Multiple Family, Institutional, Natural, Industrial, etc.) borders single-family residential land use, an edge is considered to be present. They found that crime is 64 percent higher in these edges than in the interior of the neighborhoods. In a similar approach, Song et al. (2015) also observed that criminal victimization rates were 2–3 times higher on the edges compared to elsewhere. These studies defined edges as where single-family zoning changes to other types of land uses (Song et al., 2013; 2015). Yet, changes from non-residential land use (i.e., retail) to another type (residential, office, industrial land use etc.) should be considered as well. Although relatively infrequent, there are predominant retail, office, industrial, or other land use areas in a city. At the border of two or more areas with different land use characteristics, people may have cognitive distinctions between them. Simply ignoring the changes from non-residential land use to another might lead to less comprehensive results. In sum, we hypothesize that street segments with greater difference of land uses between the two sides of the street will have higher risk of crime.

We emphasize that our measure of a land use boundary is conceptually distinct from a measure of land use mix. Indeed, studies have measured the general land use mix in small geographic units (Wo 2019, 2019; Browning et al. 2010; Taylor et al. 1995), with some positing that such mixing of land use may actually result in lower rates of crime due to enhanced eyes on the street posited by Jane Jacobs (1961). Our measure is distinct in that we are explicitly measuring the difference in land use mix across the two sides of the street. Although there is certainly some overlap in these measures, we show below that they are in fact quite empirically distinct in our study area. Furthermore, we argue that there is a conceptual distinction as the clustering of different land uses on the two sides of the street might operate as a boundary, as opposed to the posited effects that would occur from general land use mixing. Again, in this view, it is residents' perceptions that interpret these differences—when they occur across the two sides of the street—as having important implications for a sense of cohesion and hence willingness to engage in informal social control activity that can enhance guardianship.

Social Boundaries

We posit that social boundaries are as important as physical boundaries for understanding the spatial patterns of crime, and test this here. We define social boundaries as socioeconomic and racial differences that exist across the two sides of the street segment. Given the definition of a street segment (both sides of a street between two intersections), there are possible perceptual differences for residents when there are differences in the socioeconomic or racial composition between one side and the other of a street segment (Tajfel and Turner 1986). In these cases, we posit that the street segment can act as a social boundary if it impacts residents' perceptions given the differences across the two sides of the street. The two sides of the street might then be considered two geographically distinct areas based on the center line of the street. Thus,

measuring the socioeconomic characteristics and racial composition of each side of the street segment may act as a social cognitive barrier that can be recognized as spatial social boundaries.

Again, we highlight that our measure is distinct from a measure of general racial/ethnic mixing. Studies commonly construct a measure of racial/ethnic mixing—often referred to as a heterogeneity measure—with the expectation that it will be associated with higher rates of crime (Hipp 2007, 2007; Morenoff, Sampson, and Raudenbush 2001; Sampson and Groves 1989). The logic is based on social disorganization theory, in which such racial/ethnic differences are posited to reduce the number of social ties among residents, which would then result in less informal social control and therefore higher rates of crime. Although we also posit that our measure of racial/ethnic difference across the two sides of the street will also be associated with higher rates of crime, we posit a slightly different mechanism. That is, we posit that when such racial/ethnic differences occur across the two sides of the street they will be perceived as a boundary. It is possible that they will not only impact the social relations between residents on the same block (Legewie 2018), but will also impact residents' *perceptions* about cohesion. Furthermore, it may also impact social ties across a broader area (Kim and Hipp 2019; Boessen and Hipp 2015; Hipp and Boessen 2013). We show in our study that general racial/ethnic mixing is empirically distinct from our racial/ethnic differences boundary measure.

We therefore posit that these social differences across the two sides of the street can impact residents' perceptions of the extent to which those on the other side truly are part of the same social environment. Although residents can certainly walk across the street to still interact with such neighborhoods, we posit that perceptual differences can occur in these cases that therefore impede social interactions and the formation of informal social control among residents living on one and the other side of a street segment. Particularly, residents living on one side of a

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street segment might feel that the other side is not part of their own space if the qualities of socioeconomic status or racial composition between two sides are too dissimilar. Then, social ties, cohesion, and the level of informal social control among the residents across the street may be weakened, which may lead to increase in the risk of crime. Indeed, Legewie (2018) found that areas measured as a higher level of a racial boundary were at higher risk of violent crime even controlling for other types of physical boundaries. He employed an areal wombling technique to identify the spatial boundaries of racial composition for census blocks in Chicago. He found that a one standard deviation increase in the composite measure for neighborhood racial boundaries corresponds to 8 percent higher risk of violent crime. Our approach differs somewhat in that we posit that street segments are a more appropriate unit of analysis, and that differences across the two sides of the street will be conceptually important.

Moderating Effects between Physical and Social Boundaries

The effects of social boundaries on crime may be moderated by physical boundaries. We expect that physical boundaries would impact crime because they can provide hints to offenders about the general accessibility to and relative attractiveness of places for the commission of crime. However, for the same reasons, physical boundaries may moderate the effects of certain social boundaries also. Physical boundaries may strengthen the crime enhancing effects of certain social boundaries. The presence of physical boundaries may highlight the existing social distances, and therefore exacerbate the crime enhancing effects of social boundaries. For example, areas with higher level of socioeconomic and racial differences across the two sides of the street may have challenges facilitating social cohesion and ties among residents, and such

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boundary differences may be heightened by the presence of a physical boundary in which there is greater land use mix across the two sides of the street.

Brantingham and Brantingham (1993) also suggested that since areas near spatial edges may contain structural characteristics that bring about less informal social control in communities, there can be less surveillance by stable residents who are committed to keep their community safe. On the other hand, effects of socioeconomic and racial difference at the street segment level may be more pronounced in the areas without a land use difference physical boundary. This implies a type of “crowding out” effect in which the presence of a physical boundary *detracts* from the social boundary effect, and therefore diminishes the otherwise negative impact of the social boundary. A consequence is that a social boundary in the context of no physical boundary based on land use differences would have the strongest impact on local crime rates. These considerations suggest that the characteristics of social boundaries may interact with the physical boundaries to shape human activity and thus moderate crime patterns. Therefore, the present study considers possible interactions between our measures of physical and social boundaries.

Data and Methods

The current study examines edges in urban settings and the spatial patterns for crime at the street segment level using data from 117 cities in the Census-defined urbanized area within Los Angeles County. The unit of analysis is the street segment – both faces of a street between two intersections. Street segment is a unit of analysis widely employed in previous studies of criminology of place (Groff, Weisburd, and Yang 2010; Weisburd 2015; Weisburd, Groff, and Yang 2012, 2014; Weisburd et al. 2017; Weisburd, White, and Wooditch 2020; Hipp and Kim

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2019; Kim 2018; Kim and Hipp 2017, 2019). We decided to use the street segment as a unit of analysis based on theoretical and methodological merits by its definition – both sides of a street between two intersections. The Brantinghams (1993) defined edges as spatial boundaries that can separate an area into two different sides. We acknowledge that street segments are small communities that contain shared social structural characteristics and routine activities across the two sides, yet it is also true that they might function as spatial boundaries if they change residents' perceptions in instances in which there are differences of social or physical properties on the two sides. The primary motivation for the current study is to empirically examine this research question to see if street segments actually function as physical and social edges.

In the current study, we operationalized the physical boundary as land use difference between the two sides of the street, and social boundaries as the difference of racial composition or socioeconomic status between the two sides of the street segment. We utilize land use datasets from the Southern California Association of Governments (SCAG) in 2008 to identify which land parcels belong to which sides of a street segment based on their spatial locations as well as a physical boundary measure (land use difference between the two sides of a street segment). We used Los Angeles County (LAC) Land Parcel Data in 2010 to capture home value difference, which captures socioeconomic differences between the two sides of a street segment. We employed 2010 Census block data to measure racial boundary measures. We control for three other types of physical boundaries: freeways, rivers, and park boundaries using the data from 2010 Environmental Systems Research Institute (ESRI) street map data. We also account for structural characteristics in street segments using 2010 Census block data.

<<< Figure 1 about here >>>

Physical and Social Boundary Measures – Difference between the Two Sides of Street Segment

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Measures of physical boundaries on the segment

We create our difference measures between the two sides of a given segment by calculating the differences of physical or social characteristics between the blocks in each side of the segment. To do so, we first identify spatial associations between blocks and street segments using land parcels. For example, in Figure 1, a land parcel, $p1$ has the block identification of block A because it has its centroid within block A , whereas parcel $p13$ has block identification of block B for the same reason. All parcels are associated with the contiguous street segment and the blocks they are located within. Then, they are aggregated to the street segment and block levels. The entire process identifies the parcel-block and parcel-segment associations with a side of the street segment. We can then aggregate the measure of interest to the block-segment on which it is located, and we therefore end up with segment/block combinations that refer to each side of the street segment.

Using this information, we measure the difference of land use (a physical boundary) based on proportions of five land use types in blocks on both sides of a street segment (i.e., residential, retail, office, industrial, and other). We computed the physical and social difference measures between the blocks on two sides of a street segment (block A and Block B in Figure 1). This general approach is also used for the social boundary measures, and these measures take the following form:

$$D_a = \sqrt{\sum_{k=1}^K (Xa_{ik} - Xa_{jk})^2} \quad (1)$$

where, in this case, D_a represents the difference across the street in terms of land use of a segment a , Xa_{ik} refers to the percentage of a particular type k (i.e., a specific land use category, and Xa_{jk} is that on the j side of segment a . This measure theoretically ranges from 0 to 141 for

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the land use and race/ethnicity measures. By taking the square root of this sum of the squares to return the measure closer to the initial metric.¹

We use these same data and also account for the land use characteristics of a street segment in the more traditional manner. We included measures capturing the proportion of land use on a segment composed of these same five different land use characteristics: 1) percent retail land use; 2) percent office land use; 3) percent industrial land use; 4) percent residential land use. The remaining land uses (“other”) are the reference category. We also constructed a measure of land use mix based on the Herfindahl index of the proportions of these same land use categories. We therefore make a distinction between general land use mix on a street segment, and the difference in land use composition between the two sides of the street (which is our measure of a physical boundary).

Measures of social boundaries on the segment

We also created measures of social boundaries based on the difference of home values or racial composition (social boundaries). For the measure of difference based on home values, we used the 2010 LAC Land Parcel Data to located parcels on a specific block-segment. These data provide the assessed value of a home, along with the year of the assessment. Given that assessments in California typically only occur when a sale occurs on a parcel, we needed to adjust these values appropriately. We accomplished this by estimating a hedonic regression model in which the logged assessed value is regressed in an indicator variable of the year of assessment as well as the logged lot square footage, number of bedrooms, number of bathrooms, the logged unit square footage, and polynomials for each of these measures to capture

¹ Note that we could have instead computed the absolute value of the difference, rather than squaring the difference. The two approaches will generally return similar results. Our approach weights differences more heavily (given that they are squared), which we believe is theoretically desirable since larger differences would presumably be more apparent to residents and therefore impact their perceptions of differences.

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nonlinearities. The predicted value for each unit is then used as the value in the current year (since this is the excluded year indicator variable in the model). With this information, we then assigned these values to the proper block-segment, and computed the average home value on each side of the street. We then construct our difference measure similar to equation 1. To assess whether this difference across the two sides of the street in home values has a distinct effect, we used these same data to construct measures of the average home value and the inequality in home values on the street segment. Using the home values adjusted for year of assessment, we constructed a measure of *average home value (logged)* in the street segment. To create a measure of *home value inequality*, we computed the standard deviation of home values on the street segment.

The other social boundary we constructed at the street segment level captured the difference in racial/ethnic composition. Constructing the measure is more challenging than our other segment boundary measures, given that we only have racial/ethnic data aggregated to blocks based on 2010 Census data. We therefore needed to impute these block data to the particular side of the street segment. Note that typically a block will have four sides of street segments associated with it (see Figure 1). We utilized two different approaches to imputing these data using extremely different assumptions to assess the sensitivity of our results. The first approach assumes that the block data is equally apportioned to all the segment-blocks that it is associated with. This is the approach that Kim (2018) adopted and referred to as the Simple Average (SA) approach. It assumes no segregation at these smaller street segments compared to the block. The second approach assumes that the block racial/ethnic data is apportioned to the segment-blocks such that there is maximal segregation to the segment-blocks. In this approach,

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we distribute the racial/ethnic group proportions in the focal block to the segment-blocks relative to the proportions in the adjacent blocks. This implies:

$$P_{gik} = P_{gi} * (P_{gk} / \bar{P}_{gk})$$

where P_{gik} is the proportion of group g in segment-block ik , P_{gi} is the proportion of group g in block i , P_{gk} is the proportion of group g in adjacent block k , and $\bar{P}_{gk}$ is the average proportion of group g in the k blocks adjacent to block i .

To demonstrate the approach, consider a stylized example with just two groups (to simplify things) in which a focal block has 50% of each group, and the four nearby blocks have 30%, 70%, 90%, and 90% of Group A, respectively. Whereas the SA approach would assign 50% Group A to each of the four segment-blocks adjacent to the focal block, this approach instead assigns 21.5%, 50%, 65%, and 65% Group A to each of the segment-blocks. This is because the average nearby block is 70% Group A ($280\% / 4$), and the assigned weight for each of the blocks is .429 ($30/70$), 1 ($70/70$), 1.286 ($90/70$), and 1.286 ($90/70$), as the percent Group A in each block is divided by this average. Then this weight is multiplied by the percent Group A in the focal block (50%) to create the value assigned to each segment-block. This same calculation is done for all the segment-blocks and blocks in the city. Once we have apportioned the five racial/ethnic groups to each segment-block (i.e., White, Black, Hispanic, Asian, and Others), we then construct our difference measure similar to equation 1. We compare the results using these two different imputation strategies for creating our racial/ethnic boundary measure.

To assess whether the effects we detect are indeed due to our racial/ethnic boundary measure, we also included controls of the racial/ethnic composition and general racial/ethnic mixing. We control for the presence of racial/ethnic minorities in street segments as the percent African American and the percent Latino/Hispanic. To capture the level of racial/ethnic

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heterogeneity, we compute a Herfindahl index based on five racial/ethnic groups (white, African American, Latino, Asian, and other races). Note that, analogous to our land use mix and land use physical boundary, this heterogeneity measure captures the mixing of racial/ethnic groups on a street (regardless of location of the household), whereas our social boundary measure explicitly measures the difference in the racial/ethnic composition of households living on the two sides of the street.

Traditional boundary measures – Freeways, Rivers, and Parks

We also take into account three more traditional types of physical boundary measures: freeways, rivers, and park boundaries. The freeways, rivers, and parks boundary data come from 2010 Environmental Systems Research Institute (ESRI) street map data. The freeway data include highways and interstates. Rivers are defined by named rivers and streams. Parks are national, state, and local parks. We classify a street segment as being on the boundary of interest if the Euclidean distance from the segment centroid to the city border is less or equal to 10 meters. This means the segments within a 20-meter (65 feet) buffer are considered being on the edge (Kim and Hipp, 2017).

Structural Characteristics Control variables

We included a set of variables that account for the effects of social environment (structural characteristics) of the street segments. For these measures, we imputed 2010 Census block data to the street segment level using the simple average (SA) imputation method proposed by Kim (2018). The SA is the average value of the adjacent blocks that are apportioned to the street segment; Kim (2018) found this approach to be generally valid compared to data actually collected at the street segment level.² Besides the variables mentioned earlier, we use the percent

² Kim (2018) proposed the imputation approach given the difficulty of collecting segment-level data. Although it is ideal to have data at the segment level, the question is whether the imputation methods are effective despite their

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home owners to measure *residential stability* and the percent *occupied units* to measure vacancies in place. We also account for the prime offending ages by including a measure of the percent aged between 15 and 29.

Dependent Variables

The dependent variables are the number of violent and property crime incidents. The crime data come from the Southern California Crime Study (SCCS).³ These are official crime data from police agencies of cities with geographic information such as addresses or 100 blocks. SCCS classified crime events into violent crime and property crime. Crime events were geocoded for each city separately to latitude–longitude point locations using ArcGIS 10.2, and subsequently aggregated to street segments. We used the average of violent and property crime incident data in 2010, 2011, and 2012 at the street segment level. The geocoding hit rate was about 97% over all cities included in the current study.

Analytic strategy

Since the dependent variables of the current study are counts of crime events (violent and property crime), their distributions are not likely to be normally distributed. Accordingly, negative binomial regression, which effectively deals with over-dispersion, is used in the current study (Osgood 2000). We also included a dichotomous variable for each city, which allows us to capture changes of crime *within* a particular city. We included spatially lagged measures to account for the structural characteristics in the surrounding areas. These measures were created based on an inverse distance function with a cutoff at $\frac{1}{4}$ mile around each street segment. The

imperfections. Kim's (2018) sensitivity analysis using point level home value data attempts to do this, and found that the imputation methods work fine at least in the study area and for the home values as proxy measures of socioeconomic status of the places.

³ For more detailed information on the SCCS, please refer to <https://ilssc.soceco.uci.edu/category/crime-report/>

Edges

resulting spatial weights matrix (W) is row standardized. This matrix is multiplied by the matrix of values in the blocks for the variables of interests. We estimate a series of negative binomial regression models in which measures of the physical and social boundaries discussed above are included while controlling for the effects of structural characteristic measures. The general form of these models are

$$E(y) = \exp(\alpha + B_1\mathbf{X} + B_2\mathbf{S} + B_3\mathbf{WS} + B_4\mathbf{C}) \quad (2)$$

where y is the dependent variable to be explained (the number of crime events), α is an intercept, $\mathbf{X}$ represents a matrix of various measures of physical and social boundaries in the models, $\mathbf{S}$ is a matrix of the structural characteristic variables, $\mathbf{WS}$ is a matrix of the spatially lagged structural characteristic measures, and $\mathbf{C}$ is a matrix of the dummy variables for cities. The full model includes all physical and social boundary measures, simultaneously. Summary statistics of the variables included in the current study are reported in Table 1. Also, we detected no issue of multicollinearity as the variation inflation factor (VIF) scores for the models did not exceed a value of 5.

<<< Table 1 about here >>>

Results

To check how many street segments have homogenous/heterogenous physical and social characteristics on the two sides, we checked the distributions of the social boundary scores across streets (difference in racial and home value scores) as well as the physical boundary score (land use difference). Figure 2 describes the distributions of the physical and social boundary measures. We observed that about 25-35 percent of the street segments in our sample have homogeneous land use, home value, or racial compositions on both sides, while the remaining

Edges

65-75 percent have some variation between the two sides. This implies that street segments have some aspects of edges as some of them have heterogeneous physical and social properties on both sides, although many of them still share homogenous characteristics on both sides.

<<< Figure 2 about here >>>

Figure 3 is a map of Los Angeles City with street segments colored according to the level of land use difference at the street segment level. Note that although our study area is the Census-defined urbanized area within Los Angeles County we zoomed into Los Angeles city for purposes of a better map extent. Red streets show the highest level of land use difference, whereas blue streets indicate areas with low land use difference. As shown, there is some variation in terms of land use difference between the two sides of street segments. Also, we observe that red streets generally represent the outer boundaries of space in the city of Los Angeles in terms of land use changes, whereas blue and green streets are located in the interior areas. Thus, the land use difference between the two sides of a street segment can be a plausible alternative to properly measure peripheral areas.

<<< Figure 3 about here >>>

Next, to systematically assess whether our approach of calculating the difference between the two sides of a street can capture (dis)similar qualities compared to a method simply measuring the physical and social environmental features, we viewed the correlations between our physical and social boundary measures at the street segment level and the corresponding measures of land use mix, racial/ethnic heterogeneity, and concentrated disadvantage. The land use physical boundary measure and the land use mix measure are correlated .51, implying considerable empirical difference in the two measures. The racial/ethnic social boundary measure is correlated just .31 with the racial/ethnic heterogeneity measure, which again implies

Edges

considerable differences in what these two measures are capturing. There are clearly empirical differences between measuring the general mixing on a street segment and the difference of those measures between the two sides of street. Furthermore, the social boundary measure of home value was correlated just 0.2 with the measure of *home value inequality* in the street segment.

Main Effects

Next, we turn to the estimated models with our boundary measures. As hypothesized, we observed positive relationships between all three of these boundary measures and violent and property crimes. For instance, a one standard deviation (SD) increase in land use difference across the street segment results in an 8.8 percent ($\exp(\beta \times \text{SD}) - 1$) increase in the risk of robbery. Likewise, a one SD increase in land use difference enhances the risk of burglary and motor vehicle theft about 4.5 percent and larceny about 2 percent. This confirms that street segments with higher level of land use difference between the two sides have higher risk of violent and property crime. Note that we obtained this effect even controlling for other features of the land use. A street segment with one standard deviation more land use mix in general is expected to have 6.2 and 58.3 percent more aggravated assault and robbery, respectively, but is not expected to have higher rates of the other crime types. We also controlled for land use composition, and see that measures of percent retail and office land use are positively associated with crime, whereas the percent residential and industrial land uses show mixed findings with crime rates.

<<< Table 2 about here >>>

Next, we turn to the findings of our social boundary measures. First, we observed that street segments with higher level of housing value difference between the two sides of a street

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are at higher risk of violent and property crimes in general. For instance, a one SD increase in difference across the street is associated with about 2 and 4 percent higher risk of aggravated assault and robbery, respectively. Similarly, a one SD increase in home value difference (socioeconomic boundary) results in 1.5, 3, and 4.6 percent higher risk of burglary, motor vehicle theft, and larceny, respectively. Note that this effect is detected even when controlling for the average home values on a street segment, which are positively associated with crimes, which may indicate an opportunity effect in which such locations provide more targets (Hipp 2007). It is also detected when controlling for general home value inequality, which exhibits a strong effect: a one standard deviation increase in home value inequality is associated with 13 and 11 percent higher risk of aggravated assault and robbery, and 10, 12.5, and 19.5 percent higher risk of burglary, motor vehicle theft, and larceny, respectively.

We observed similar patterns for the racial difference between the two sides of the street segment. That is, a higher level of racial difference leads to higher risk of violent and property crimes, in general. For instance, a one SD increase in racial difference is associated with 2 and 4.5 percent enhanced level of aggravated assault and robbery, respectively. For property crime types, a one SD increase in racial boundary measure is related to 3 and 2 percent higher risk of motor vehicle theft and larceny, respectively, in street segments. Notably, the racial/ethnic heterogeneity measure of the street segment has a negative association with robbery, indicating that there is something important about distinguishing between the characteristics of the two sides of the street, rather than just measuring the general level of racial/ethnic mixing. We also find that the percent Black and percent Latino in street segments have positive associations with violent crime. Note that Table 2 reports the findings of racial difference measure using the second imputation strategy that explicitly distributes the racial/ethnic group proportions in the

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focal block to the segment-blocks relative to the proportions in the adjacent blocks. We reported the same models with the SA imputation approach in Appendix Table A1 and observed that the findings are not substantially different.⁴

Next, we turn to the coefficients for the three more conventional measures of physical boundaries. There are strong effects for being adjacent to freeways and park boundaries as such segments have higher levels of crime. For instance, a street segment that is adjacent to a freeway has 30 and 87 percent more aggravated assaults and robberies, respectively, than a segment that is not adjacent to a freeway. And a segment adjacent to a freeway also has 44 percent more burglaries, 56 percent more motor vehicle thefts, and 62 percent more larcenies. Also, segments on park boundaries have 55, 69, and 46 percent higher risk of aggravated assault, robbery, and larceny, respectively. However, we see less evidence of a boundary effect for rivers. Finally, we briefly describe the findings of the structural characteristics. Population has a positive association with all types of crime, but the fact that the coefficient is less than one indicates that the crime rate increases more slowly than the population. The percent home owners and the percent occupied units are negatively associated with all crime types. The social-demographic variables tend to have similar relationships with crime when measured at the broader spatial lag $\frac{1}{4}$ mile area rather than the street segment.

Moderating Effects

Given the robust relationships we detect between our novel physical and social boundary measures with rates of crime, we next wished to assess whether the relationship of these social boundaries measures with crime rates in street segments is moderated by our land use difference physical boundary measure. Tables 3 and 4 show the interaction coefficients for the two social boundary measures and the land use difference measure. We have plotted the predicted values of

⁴ We found that these two approaches yield racial boundary measures that are highly correlated (0.93).

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crime in Appendix Figures A1-8 according to the coefficient results of the interaction term and the main effects at varying levels of the land use difference measure (Low = -1 SD, Med = mean, and High = +1 SD). The patterns of home value difference for various crimes are plotted in Appendix Figures A1-4 and those of racial difference in Appendix Figures A5-8. We present in the text in Figures 4 and 5 the results for robbery, which are representative of the plots for all crime types.

<<< Tables 3 and 4 about here >>>

In the interaction models looking at home value boundaries, we do not find evidence that the crime-enhancing effect of the home value boundary measure is more pronounced on a segment with a sharper physical boundary. Instead, although we observe in Figure 4 that a segment with a stronger home value boundary has more robberies, and one with a sharper physical boundary has more robberies, the two features together exhibit a crowding-out effect. Thus, whereas there will be more robberies in a segment as the socio-economic boundary becomes sharper, this increase is even greater if the socio-economic boundary occurs in a segment without a physical boundary (orange line). Nonetheless, segments at the greatest risk of robberies are those with both a physical boundary and a socio-economic boundary. The pattern is generally similar for the other crime types. Furthermore, the pattern is similar for the racial boundary measure, as the effect of racial difference at the street segment level is moderated by the physical boundary (land use difference). For example, we observe that the risk of robbery increases as the racial boundary measure increases (Figure 4), and this crime-enhancing pattern is more pronounced in street segments with low land use difference. In sum, the interaction results show that the crime-enhancing effects of social boundaries appear to matter more in areas without a physical boundary.

<<< Figures 4 and 5 about here >>>

Discussion

Although previous studies have theorized the importance of physical and social boundaries (edges) in understanding crime in place, the relationship between edges and the level of crime has been less studied empirically. We accounted for the conventional physical boundary measures of highways, parks, and rivers. However, a novel contribution was our boundary measure of land use difference, as well as our social boundary measures of socioeconomic and racial difference between the two sides of a street segment. The results indicated that physical and social boundaries are important to consider in understanding the spatial patterns of crime. Therefore, one primary contribution of the present study is empirically testing the importance of various types of physical and social boundaries for crime in place.

First, we observed that our measure of a physical boundary—land use difference between the two sides of a street segment—results in higher risk of violent and property crime. As theorized, the results imply that the land use difference can be a cognitive edge which may affect the level of informal social control. Potential offenders might find more criminal opportunities in the peripheral areas because such areas are less likely to be considered as core parts of someone's activity space. Consequently, there will be less territoriality and people may feel less responsible for the surveillance; and thus lower levels of guardianship will result in this place. We highlighted that this was not simply a land use mix effect, as our measure was conceptually distinct from a typical land use mix measure, and showed a distinct relationship with crime rates. There appears to be something distinct about cases when the land use characteristics differ between the two sides of the street, rather than just a general mix of land use on the street

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segment. Future research might extend this pattern further by empirically examining the resident's cognitive perception of edges by the land use difference between two sides of the street and the level of informal social control. For example, it is still unclear how people actually distinguish between the peripheral or central part of a physical area, and how the level of informal social control is related to the exterior or interior locations of the space.

Our findings of social boundaries showed that street segments with higher levels of socioeconomic and racial differences between the two sides are at higher risk of violent and property crime. The results for the racial difference measure were consistent with a previous study that measured the racial boundaries based on census blocks (Legewie, 2018). As theorized, this might be because of reduced social cohesion and informal social control in areas near social boundaries due to lower social porosity with more pronounced socioeconomic and racial difference between the two sides of the street, which may act as cognitive social barriers among residents. It was notable that a measure of racial/ethnic mixing on the street segment showed a modest opposite relationship with crime; again, it appears that there is something important about the *difference* in racial/ethnic composition across the two sides of the street segment that is conceptually different from general racial/ethnic mixing on the street segment. The fact that racial/ethnic heterogeneity in the buffer had the expected positive relationship with crime indicates that this general mixing effect may operate at this larger scale (Hipp 2007). This suggests that even if social boundaries are less visible than physical boundaries, social boundaries are important to consider for understanding spatial patterns of crime along with physical boundaries.

Although scholars have recognized the importance of non-visible boundaries in urban settings (Brantingham and Brantingham 1993; Kim and Hipp 2017), relatively less attention is

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paid to social boundaries. Therefore, the current study primarily contributes to the field by considering both physical and social boundaries as important urban spatial features that might have direct relevance to explaining crime in place. Also, we introduced a method to measure social boundaries based on the difference between the social characteristics on the two sides of the street, which is another methodological and theoretical contribution of the present study. We hope future research adapts this method to measure various types of social boundaries. For example, our method is applicable to measure ethnic-immigrant boundaries by calculating the difference of immigrant population or ethnic business characteristics between the two sides of a street segment.

Our findings of moderating effects between social boundaries (socioeconomic and racial difference) and physical boundary (land use difference) found evidence that these different types of boundaries exhibit crowding-out effects for crime, rather than synergistically working together. Thus, focusing exclusively on a single type of spatial boundary may capture an incomplete association between spatial boundaries and crime in place. Implications from the results are twofold: (1) areas with high levels of both social and physical boundaries are at higher risk of crime; yet (2) the crime enhancing effects of social boundaries tend to be more pronounced in street segments without a land use difference physical boundary. We theorized that areas with social boundaries in terms of socioeconomic status and racial composition will have lower levels of informal social control due to a lack of social porosity. It appeared that the crime-enhancing effects of social boundaries were more pronounced on segments *without* physical boundaries, which may imply that these physical boundaries can “crowd out” the effect of a social boundary. It may be that the presence of a physical boundary is obvious enough that

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any social boundary impacts simply do not play out in such an environment. Nonetheless, why this occurs we cannot be entirely certain, and should be a direction for future research.

The current study is not free from limitations. First, it is still unclear how various social and physical boundaries can actually enhance crime in street segments, which is beyond the scope of the present study. Similar to prior studies, we do not have the data to directly test the mechanisms that link social/physical boundaries, informal social control, and criminal opportunities in place, and therefore, integrating data to test such mechanisms would be an obvious extension. Nevertheless, we believe that testing the overall effects of social/physical boundaries at the street segment level and spatial crime patterns without the mediator still provides unique theoretical and methodological contributions as discussed above. We hope future research focuses on the specific mechanisms between the presence of spatial boundaries across the two sides of a street, and the level of crime in place. Second, ours was a cross-sectional study. Future research might test how changes in the location of edges over time can affect spatio-temporal patterns of crime. Although most features likely remain quite stable over time, other physical and social boundaries might change their locations and characteristics. For instance, land use difference at the street segment can be changed as land use planning policies change over time. Social boundaries are also subject to change because of urban planning and administrative policy changes over time, as well as mobility patterns. Therefore, a study looking at how the changes in edges over time can impact changes in crime is necessary.

In conclusion, the present study examined the relationships between various types of physical and social boundaries and crime in street segments. We empirically tested and found that traditional physical boundary measures such as highways and parks generally exhibited a positive relationship with crime, although a measure of rivers was not significant. Importantly,

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we tested and found that our novel physical boundary measure of land use difference at the street segment level exhibited a positive relationship with most crime types. We also tested segment-level social boundary measures of socioeconomic and racial difference between the two sides of a street segment. We found that street segments with these social boundaries consistently have higher rates of violent and property crime. Furthermore, we found that our social and physical boundary measures, rather than reinforcing one another, instead appeared to exhibit crowding-out effects in which they limited the effects of each other. Our results indicate that although much empirical research focuses solely on physical boundaries *between* street segments, our measures of social and physical boundaries *within* street segments have important consequences for the spatial location of crime, and therefore are worthy of further research.

References

- Boessen, Adam, and John R. Hipp. 2015. Close-ups and the scale of ecology: Land use and the geography of social context and crime. *Criminology* 53 (3):399-426.
- Brantingham, P. L., and P. J. Brantingham. 1978. A Topological Technique for Regionalization. *Environment and Behavior* 10 (3):335-353.
- Brantingham, P. L., and P. J. Brantingham. 1975. Residential burglary and urban form. *Urban Studies* 12 (3):273-284.
- . 1993. Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology* 13:3-28.
- Brantingham, P. L., P. J. Brantingham, M. Vajihollahi, and K. Wuschke. 2009. Crime Analysis at multiple scale of aggregation: A topological approach. In *Putting Crime in Its Place: Units of Analysis in Geographic Criminology*, edited by D. Weisburd, W. Bernasco and G. J. N. Bruinsma. New York, NY: Springer.
- Browning, C. R., Reginald A. Byron, Catherine A. Calder, Lauren J. Krivo, Mei-Po Kwan, Jae-Yong Lee, and Ruth D. Peterson. 2010. Commercial density, residential concentration, and crime: Land use patterns and violence in neighborhood context. *Journal of Research in Crime and Delinquency* 47 (3):329-357.
- Groff, E., D. Weisburd, and S. M. Yang. 2010. Is it Important to Examine Crime Trends at a Local "Micro" Level?: A Longitudinal Analysis of Street to Street Variability in Crime Trajectories. *Journal of Quantitative Criminology* 26 (1):7-32.
- Hipp, John R. 2007. Block, Tract, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point. *American Sociological Review* 72 (5):659-680.
- . 2007. Income inequality, race, and place: Does the distribution of race and class within neighborhoods affect crime rates? . *Criminology* 48 (3):683-723.
- Hipp, John R., and A. Boessen. 2013. Egohoods as waves washing across the city: A new measure of neighborhoods. *Criminology* 51:287-327.
- Hipp, John R., and Young-An Kim. 2019. Explaining the temporal and spatial dimensions of robbery: Differences across measures of the physical and social environment. *Journal of Criminal Justice* 60:1-12.
- Kim, Young-An. 2018. Examining the Relationship Between the Structural Characteristics of Place and Crime by Imputing Census Block Data in Street Segments: Is the Pain Worth the Gain? *Journal of Quantitative Criminology* 34 (1):67-110.
- Kim, Young-An, and John R. Hipp. 2017. Physical Boundaries and City Boundaries: Consequences for Crime Patterns on Street Segments? *Crime & Delinquency* 64 (2):227-254.
- . 2019. Pathways: Examining Street Network Configurations, Structural Characteristics and Spatial Crime Patterns in Street Segments. *Journal of Quantitative Criminology*.
- . 2019. Street Egohood: An Alternative Perspective of Measuring Neighborhood and Spatial Patterns of Crime. *Journal of Quantitative Criminology*.
- Kubrin, Charis E., and Ronald Weitzer. 2003. New Directions in Social Disorganization Theory. *Journal of Research in Crime and Delinquency* 40 (4):374-402.
- Legewie, Joscha. 2018. Living on the Edge: Neighborhood Boundaries and the Spatial Dynamics of Violent Crime. *Demography* 55 (5):1957-1977.
- Morenoff, J. D., R. J. Sampson, and S. W. Raudenbush. 2001. Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology* 39 (3):517-559.
- Osgood, D. Wayne. 2000. Poisson-based regression analysis of aggregate crime rate. *Journal of Quantitative Criminology* 16 (1):21-43.
- Sampson, R. J., and B. Groves. 1989. Community Structure and Crime: Testing Social-Disorganization Theory *American Journal of Sociology* 94 (4):774-802.
- Sampson, R. J., S. W. Raudenbush, and F. Earls. 1997. Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science* 277 (5328):918-924.
- Song, J., Martin A. Andresen, Patricia L. Brantingham, and Valerie Spicer. 2015. Crime on the edges: patterns of crime and land use change. *Cartography and Geographic Information Science*:1-11.
- Song, Justin, Valerie Spicer, and Patricia Brantingham. 2013. The edge effect: Exploring high crime zones near residential neighborhoods. Paper read at Intelligence and Security Informatics (ISI), 2013 IEEE International Conference on.
- Tajfel, Henri. 1981. *Human Groups and Social Categories: Studies in Social Psychology*. Cambridge: Cambridge University Press.

- Tajfel, Henry, and John C. Turner. 1986. The social identity theory of intergroup behavior. In *Psychology of intergroup relations*, edited by S. Worchel and W. G. Austin. Chicago: Nelson-Hall.
- Taylor, R. 1997. Social order and disorder of street blocks and neighborhoods: Ecology, microecology, and the systemic model of social disorganization. *Journal of Research in Crime and Delinquency* 34 (1):113-155.
- Taylor, R., Barbara A. Koons, Ellen M. Kurtz, Jack R. Greene, and Douglas D. Perkins. 1995. Street Blocks with More Nonresidential Land Use Have More Physical Deterioration: Evidence from Baltimore and Philadelphia. *Urban Affairs Review* 31:120-136.
- Turner, John C. 1987. *Rediscovering the Social Group: A Self-Categorization Theory*. New York: Basil Blackwell.
- Weisburd, D., M. Shay, S. Amram, and R. Zamir. 2017. The Relationship Between Social Disorganization and Crime at the Micro Geographic Level: Findings From Tel Aviv-Yafo Using Israeli Census Data. *Advances in Criminological Theory* 22:97–120.
- Weisburd, David. 2015. The law of crime concentration and the criminology of place. *Criminology* 53 (2):133-157.
- Weisburd, David, Elizabeth R. Groff, and Sue-Ming Yang. 2012. *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem*. New York, NY: Oxford University Press.
- . 2014. The Importance of Both Opportunity and Social Disorganization Theory in a Future Research Agenda to Advance Criminological Theory and Crime Prevention at Places. *Journal of Research in Crime and Delinquency* 51 (4):499-508.
- Weisburd, David, Clair White, and Alese Wooditch. 2020. Does Collective Efficacy Matter at the Micro Geographic Level?: Findings From a Study Of Street Segments. *The British Journal of Criminology*.
- Wicker, Allan W. . 1987. Behavior settings reconsidered: Temporal stages, resources, internal dynamics, context. In *Handbook of environmental psychology*, edited by D. Stokels and I. Altman. New York: Wiley-Interscience.
- Wo, James C. 2019. Mixed land use and neighborhood crime. *Social Science Research* 78:170-186.
- . 2019. Understanding the Differential Effects of Land Uses on Crime: An Examination Across Philadelphia Neighbourhoods. *The British Journal of Criminology*.

Tables

Table 1. Summary Statistics

	<u>Mean</u>	<u>S.D.</u>
<i>Crime</i>		
Agg. Assault	0.13	0.43
Robbery	0.08	0.34
Burglary	0.20	0.48
M.V. theft	0.17	0.44
Larceny	0.33	1.23
<i>Boundary measures</i>		
Land use difference (divided by 100)	0.26	0.33
Home value difference	0.19	0.42
Racial difference (divided by 100)	0.17	0.19
<i>Mix measures</i>		
Land use mix	0.32	0.30
S.D. of home value	0.23	0.31
Racial/ethnic heterogeneity	0.43	0.18
<i>Control measures (Physical boundaries)</i>		
Freeways (1/0)	0.01	0.08
Park boundaries (1/0)	0.02	0.13
Rivers (1/0)	0.00	0.02
<i>Structural characteristics</i>		
Population (logged)	4.93	0.92
Average home value (logged)	9.93	5.60
Percent home owners	63.84	28.89
Percent occupied units	95.13	5.57
Percent Black	8.08	16.16
Percent Latino	40.83	30.93
Percent aged 16-29	20.50	7.83
<i>Land use measures</i>		
Percent industrial use	3.49	11.44
Percent office use	2.93	8.87
Percent residential use	74.13	28.34
Percent retail use	6.43	13.68
<i>Spatially lagged measures (1/4 mile)</i>		
Concentrated disadvantage	-0.56	8.34
Racial/ethnic heterogeneity	0.46	0.17
Percent home owners	59.13	26.25
Percent occupied units	94.97	3.74
Percent Black	7.57	14.29
Percent Latino	41.89	29.81
Percent aged 16-29	21.02	6.17

Table 2. Models of Physical and Social Boundaries and Various Types of Crime

	Agg. Assault		Robbery		Burglary		M.V. theft		Larceny	
Boundaries										
Land use difference (divided by 100)	-0.005		0.252	**	0.130	**	0.135	**	0.050	*
	-0.154		7.126		4.797		4.805		2.254	
Home value difference	0.045	*	0.098	**	0.035	*	0.068	**	0.109	**
	2.493		5.462		2.355		4.642		9.535	
Racial difference (divided by 100)	0.229	**	0.101	*	0.013		0.141	**	0.110	**
	5.736		2.382		0.394		4.067		4.055	
Mix variables										
Land use mix	0.201	**	1.540	**	-0.092		0.039		-0.044	
	2.651		18.471		-1.451		0.591		-0.849	
Standard deviation of home value	0.414	**	0.340	**	0.307	**	0.382	**	0.581	**
	18.714		14.662		16.835		21.345		36.814	
Racial/ethnic heterogeneity	0.001		-0.248	**	0.260	**	0.110		0.204	**
	0.006		-2.714		3.848		1.469		3.751	
Control measures										
Freeways (1/0)	0.266	**	0.628	**	0.370	**	0.443	**	0.481	**
	3.844		9.287		5.877		7.162		9.798	
Park boundaries (1/0)	0.438	**	0.524	**	0.055		0.029		0.381	**
	7.986		8.453		1.053		0.480		10.059	
Rivers (1/0)	-0.765		-1.263		-0.277		-0.581		-0.163	
	-1.181		-1.327		-0.827		-1.288		-0.640	
Structural characteristics										
Population (logged)	0.259	**	0.184	**	0.183	**	0.251	**	0.180	**
	23.753		15.139		21.198		26.810		25.689	
Average home value (logged)	0.032	**	0.017	**	0.053	**	0.040	**	0.035	**
	12.615		6.094		25.296		17.860		21.628	
Percent home owners	-0.008	**	-0.005	**	-0.003	**	-0.007	**	-0.005	**
	-15.781		-8.010		-6.947		-16.524		-15.789	
Percent occupied units	-0.012	**	-0.005	**	-0.002	*	-0.005	**	-0.006	**
	-15.743		-6.190		-2.060		-7.561		-11.413	
Percent Black	0.004	**	0.003	*	-0.001		-0.001		0.000	
	3.727		2.479		-0.836		-1.048		-0.586	
Percent Latino	0.010	**	0.004	**	0.001		0.003	**	0.000	
	11.017		4.799		1.327		4.638		0.155	
Percent aged 16-29	0.002		-0.002	†	0.002	*	0.002	*	0.001	
	1.196		-1.825		2.326		1.971		1.501	
Land use measures										
Percent industrial land use	-0.007	**	0.002	*	-0.002	**	0.003	**	-0.003	**
	-7.477		2.085		-2.930		4.327		-3.919	
Percent office land use	0.004	**	0.013	**	0.006	**	0.008	**	0.007	**

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	3.371		10.500		7.508		8.805		9.796	
Percent residential land use	-0.000		0.009	**	0.001		0.003	**	-0.003	**
	-0.327		9.074		0.864		4.228		-3.990	
Percent retail land use	0.011	**	0.029	**	0.008	**	0.009	**	0.012	**
	14.868		35.887		12.037		13.331		23.193	
<i>Spatially lagged measures (1/4 mile)</i>										
Concentrated disadvantage	0.039	**	0.036	**	0.012	**	0.014	**	0.004	*
	11.692		9.497		5.419		5.361		2.271	
Racial/ethnic heterogeneity	0.493	**	0.622	**	0.121		0.290	**	0.103	
	4.524		5.366		1.561		3.275		1.607	
Percent home owners	-0.002	**	-0.009	**	-0.001		-0.003	**	-0.005	**
	-3.287		-10.267		-1.216		-4.728		-10.425	
Percent occupied units	-0.014	**	-0.013	**	-0.005	**	-0.005	*	-0.004	*
	-6.207		-5.514		-2.781		-2.573		-2.241	
Percent Black	0.023	**	0.023	**	0.013	**	0.013	**	0.004	**
	17.602		17.280		12.793		11.118		4.512	
Percent Latino	0.010	**	0.009	**	-0.001		0.008	**	-0.003	**
	8.011		7.053		-1.284		8.461		-3.984	
Percent aged 15-29	-0.002		0.003		0.006	**	0.004	*	0.006	**
	-1.018		1.477		4.321		2.379		5.686	
Intercept	-2.698	**	-4.687	**	-2.142	**	-4.853	**	-1.250	**
	-10.545		-16.457		-11.187		-18.897		-7.609	
N	128532		128532		128532		128532		128532	
pseudo R-sq	0.219		0.255		0.078		0.158		0.119	

** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test)

T-values are presented below the coefficients

Fixed effects of cities are included but not shown

Table 3. Interactions: Land Use Difference and Home Value Difference

	<u>Agg. Assault</u>	<u>Robbery</u>	<u>Burglary</u>	<u>M.V. theft</u>	<u>Larceny</u>
Land use difference (divided by 100)	0.215	0.176 **	0.143 **	0.174 **	0.073 **
	0.625	4.537	4.969	5.743	3.065
Home Value difference	0.200 **	0.306 **	0.113 **	0.215 **	0.315 **
	6.035	9.262	4.035	8.170	14.533
Interaction terms	-0.177 **	-0.293 **	-0.078 *	-0.179 **	-0.225 **
	-4.120	-6.306	-2.254	-5.206	-8.257
Intercept	-2.767 **	-4.877 **	-1.943 **	-5.079 **	-1.609 **
	-10.468	-16.242	-9.772	-19.127	-9.390
N	128077	128077	128077	128077	128077
pseudo R-sq	0.218	0.254	0.076	0.157	0.111

** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test)

T-values are presented below the coefficients

Fixed effects of cities are included but not shown

All controls are included but not presented

Table 4. Interactions: Land Use Difference and Racial Difference

	<u>Agg. Assault</u>	<u>Robbery</u>	<u>Burglary</u>	<u>M.V. theft</u>	<u>Larceny</u>
Land use difference (divided by 100)	0.356	0.200 **	0.201 **	0.172 **	0.035
	1.004	5.019	6.774	5.572	1.426
Racial difference (divided by 100)	0.524 **	0.450 **	0.235 **	0.368 **	0.243 **
	8.150	6.104	4.558	6.620	5.471
Interaction terms	-0.412 **	-0.472 **	-0.533 **	-0.374 **	-0.217 **
	-4.192	-4.168	-6.252	-4.354	-3.212
Intercept	-2.736 **	-4.806 **	-1.979 **	-5.043 **	-1.527 **
	-10.368	-16.023	-9.965	-18.998	-8.936
N	128077	128077	128077	128077	128077
pseudo R-sq	0.218	0.253	0.076	0.157	0.110

** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test)

T-values are presented below the coefficients

Fixed effects of cities are included but not shown

All controls are included but not presented

Figure 1. Associations between street segment, residential parcels, and blocks

Figure 2a. Distribution of Land Use Difference (Divided by 100)

Figure 2b. Distribution of Home Value Difference

Figure 2c. Distribution of Race Difference (Divided by 100)

Edges

Figure 3. Land use difference at the street segment level in Los Angeles

Edges

Figure 4. Robbery: Interaction between home value boundary and land use difference

Figure 5. Robbery: Interaction between racial boundary and land use difference