Contested Boundaries

Explaining Where Ethno-Racial Diversity Provokes Neighborhood Conflict*

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Abstract

Concerns about neighborhood erosion and conflict in ethnically diverse settings occupy scholars, policy makers and pundits alike. But the empirical evidence is inconclusive. This article proposes the contested boundaries hypothesis as a refined contextual explanation focused on poorly-defined boundaries between ethnic and racial groups. We argue that neighborhood conflict is more likely to occur at fuzzy boundaries defined as interstitial or transitional areas sandwiched between two homogeneous communities. Edge detection algorithms from computer vision and image processing allow us to identify such boundaries. Data from 4.7 million time and geo-coded 311 service requests from New York City support our argument: complaints about neighbors making noise, drinking in public, or blocking the driveway are more frequent at fuzzy boundaries rather than crisp, polarized borders. By focusing on the broader socio-spatial structure, the contested boundaries hypothesis overcomes the "aspatial" treatment of neighborhoods as isolated areas in research on ethnic diversity.

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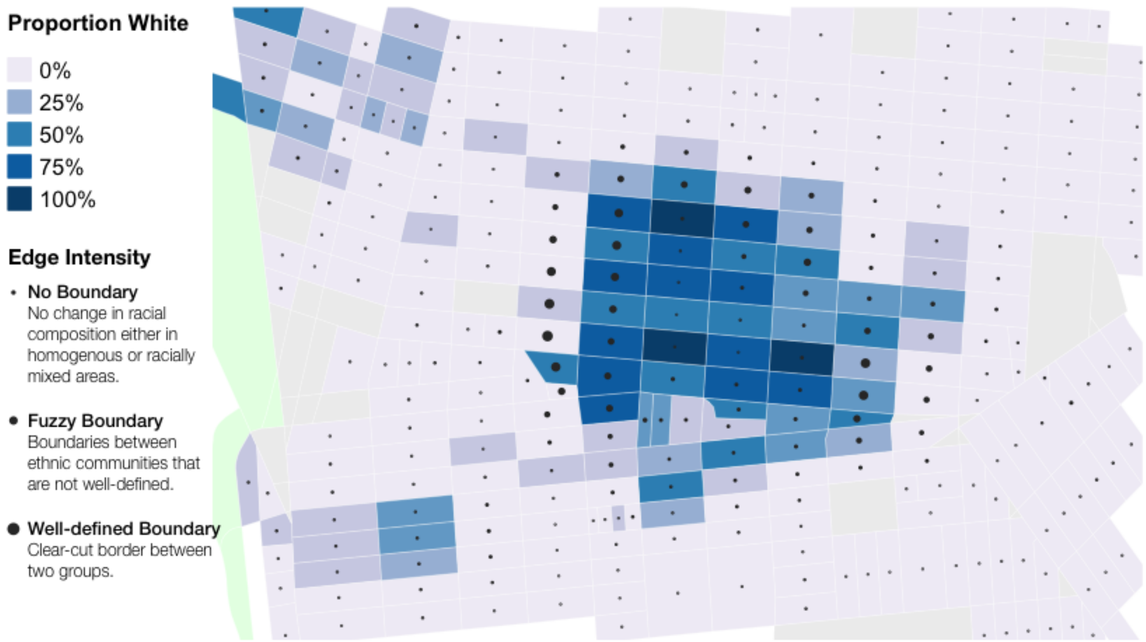
Introduction

As Western societies are growing increasingly more diverse, concerns about eroding social trust and neighborhood conflict occupy scholars, policy makers and pundits alike. At the core of this debate stands a bleak portrait of community life in ethnically diverse settings branded by mistrust, neglect for the maintenance of public goods, and withdrawal from community life. The evidence, however, is mixed. In many cases scholars find that ethnic diversity or polarization increase threat, prejudice and community erosion, but in other cases they do not. Here we propose the *contested boundaries hypothesis* as a refined contextual explanation of neighborhood conflict. We argue that neighborhood conflict arises at poorly-defined boundaries that separate ethnic and racial groups. Such fuzzy boundaries are interstitial or transitional areas sandwiched between two homogeneous communities. They are contested because they threaten homogeneous community life and foster ambiguities about group rank. Above and beyond disorganization and diverging ways of life generally found in mixed neighborhoods, their location between differently populated homogeneous communities triggers contention. Well-defined boundaries, by contrast, are accepted divisions between one group's turf and the other's and are thus less contested. By focusing on the broader socio-spatial structure, the contested boundaries hypothesis overcomes the "aspatial" treatment of neighborhoods as isolated areas in research on ethnic diversity. It highlights how residential segregation creates contentious areas at the places where groups border.

Based on this argument, we expect an inverse u-shaped relationship between edge intensity and neighborhood conflict; where *edge intensity* is a socio-spatial feature that captures changes in the composition of neighborhoods across space. It ranges from no change in racial composition (no boundary, e.g. within a homogeneous area), to gradual changes in interstitial or transitional areas (fuzzy boundaries of different strengths), and finally abrupt transitions from one group's turf to another's (well-defined or clear-cut boundaries). To measure edge intensity, we use edge-detection algorithms from computer vision and image processing. Edge detection was developed

Figure 1: Edge Intensity in Crown Heights South, Brooklyn (2010)



Note: White residents in Crown Heights South, Brooklyn, occupy an area of 24 city blocks surrounded by largely African-American residents. The edges are well-defined on the west side of the enclave but fuzzy on the north-east side.

in order to identify points in an image at which the image color or brightness changes sharply. Building on Legewie (2014), we adopt and modify this method so that it can be applied to neighborhood data allowing us to detect the borders between homogeneous areas of different ethno-racial groups. Figure 1 illustrates this concept in a detailed view of Crown Heights South in central Brooklyn, New York. It shows an area that is predominantly populated by black residents with a "white enclave" covering about 24 city blocks. Edge intensity is low (no boundary) in areas without changes in ethno-racial composition such as the parts homogeneously populated by black residents or in the middle of the white enclave. Around the 24 city blocks occupied by white residents, however, we observe well-defined boundaries on the west side of the enclave and fuzzy boundaries on the north-east and south side. The figure illustrates the continuous nature of the edge intensity scale ranging from no, to gradual, and finally abrupt changes in racial composition. These changes reflect no boundaries, fuzzy ones in different strengths, and well-defined borders. Our argument implies little tensions at the well-defined border of the west side, but increased conflict between neighbors in the interstitial areas of the fuzzy north-east and south side edges. By definition these areas are ethno-racially mixed. But according to our contested boundaries hypothesis, mixed areas that fall between homogeneous areas composed of different ethno-racial groups are more contentious than ethno-racially heterogeneous ones, per se. Our argument thus takes the local socio-spatial structure into account instead of treating neighborhoods as independent islands that are secluded from the extensive residential landscape surrounding them.

To evaluate our argument, we use process-generated data from 4.7 million time and geo-coded 311 service requests in New York City from 2010 and 2014. 311 is a centralized non-emergency telephone number, Internet platform, and smart phone application that allows city residents to file a request for or complain about issues as diverse as birth certificate services, fallen tree removal, or broken heating. Our analyses focus on complaints about neighbors as an indicator of neighborhood conflict, while adjusting for the general propensity to use the 311 system based on other service requests. Using multilevel negative binomial regression, we find a clear inverse u-shaped relation between edge intensity and the number of complaints about neighbors—a finding that is reaffirmed in various sensitivity analyses. This finding supports our argument about the importance of contested ethno-racial boundaries as an explanation of neighborhood conflict. It demonstrates that conflict is most likely to occur at fuzzy boundaries, i.e., boundaries between ethno-racial communities that are not well defined. As part of our analyses, we also find support for a number of conventional explanations based on group threat, neighborhood erosion, and social disorganization theories. These alternative explanations, do not challenge our contested boundary hypothesis, since they fail to explain the inverse u-shaped relation between edge intensity and the number of complaints about neighbors; our approach supplements existing theories. Aside from the importance of these results for the literature on intergroup relations, our research introduces contested boundaries as a theoretical concept to the growing neighborhood literature and proposes edge-detection algorithms as a corresponding measurement tool.

Ethno-Racial Composition and Neighborhood Conflict

Previous research provides a number of explanations of neighborhood conflict. Several focus on ethno-racial compositions such as ethnic polarization and heterogeneity. First, *intergroup competition* and *defended neighborhoods* theories emphasize out-group shares, out-group in-migration, or ethno-racial polarization. Second, theories about *general community erosion and disorganization* mainly focus on concentrated disadvantage and residential instability but also racial heterogeneity. These conventional approaches are established in the literature and might also explain the number of complaints about neighbors as the main outcome variable in our analysis. Equally important, they provide the background for our argument about contested boundaries as a refined contextual explanation of neighborhood conflict.

Proponents of *intergroup competition* theories have long argued that certain ethno-racial neighborhood compositions stir conflict and social tensions (Blumer 1958; Blalock 1967; Banton 1983; Olzak 1992). The approach originates from attempts to explain majority members' prejudice and discrimination against ethno-racial and immigrant minorities. According to the key insight, people feel threatened by the presence of out-group members, because of real or perceived competition between ethno-racial groups for scarce resources. The argument refers to both competition over economic interests such as jobs on the labor market or access to housing, and non-material issues such as political representation or the prevailing way of life. Many scholars see contact theory as a counterpart to intergroup competition theory, because it predicts that intergroup contact diminishes prejudices and discrimination (Pettigrew 1998). Yet in his seminal study, Allport already noted that mere casual contact "does *not* dispel prejudice; it seems more likely to increase it." (Allport 1954, p. 251; italics in the original). In a similar vein, the *defended neighborhoods* literature argues that fears of out-group in-migration from adjacent areas trigger defensive behavior among members of the dominant group to preserve a neighborhood's way of life (Suttles 1972; Rieder 1985; DeSena 1990). Based on ethnographic studies of white urban neighborhoods, this argument posits that their residents share a sense of community identity based on the exclusion of other ethno-racial groups. Building on these insights, Green et al. (1998) show that racially motivated crimes are more likely to occur in homogeneous white areas that are confronted with in-migration of ethno-racial minorities (see also Lyons 2007; Grattet 2009). Some authors have pushed beyond the focus on majority members' reactions to minority presence or in-migration. They claim that the overall most contentious situations are polarized, where two equal-sized opponents face each other (Esteban and Ray 1994; Montalvo and Reynal-Querol 2005). This is in line with Gould's (2003) argument about conflict in symmetric and asymmetric relations. Based on a wide array of settings, including murders in American cities and vengeance in nineteenth-century Corsica, Gould postulates that "conflicts are more likely to occur [...] in relatively symmetric relations in which there is ambiguity between actors concerning relative social rank, that is, asymmetries in perception that could be contested" (Gould 2003, p. XII).

A second classical line of research focuses on *general community erosion and disorganization* as a result of overall sparse networks and associated declines in social control (Shaw and McKay 1942; Sampson and Groves 1989; Taylor 2001). In addition to residential instability and concentrated disadvantage, this approach argues that ethno-racial heterogeneity is disintegrating. It results in reduced social interactions among neighbors, which again lowers overall levels of social control and capacities to solve community problems collectively. Typical work in this area focuses on neighborhood disorder (also termed incivilities) and crime (Skogan 1990; Sampson and Raudenbush 1999). This research claims that community erosion and disorganization increase overall rates of crime, including *intra*ethnic delinquencies (Hipp et al. 2009; Grattet 2009). A complementary line of research focuses on communities' capacities for collective action in pursuit of public goods, and the attitudes and expectations of trust that underlie this capacity (for an overview see Schaeffer 2014). According to the seminal study of economists Alesina et al. (1999), the proportion of tax money spent on education, trash disposal and welfare declines with increasing levels of ethno-racial heterogeneity in Unites States metropolitan areas. The debate began to receive widespread attention among sociologists and political scientists only after a study by Putnam (2007). He shows that a large number of good-community indicators suffer from ethno-racial diversity such as trust in neighbors, interest in volunteering or working on community projects, and expectations that other neighbors will do so. Putnam's findings about reduced trust in people of similar ethnicity in diverse neighborhoods situates his study in the tradition of disorganization theory and sets the debate apart from the literature on intergroup competition. In contrast to disorganization theory, this work does not only focus on reduced social interactions and lack of social control but also difficulties to balance numerous and diverse interests that reflect competing ways of life (Kimenyi 2006; Page 2008) and communication problems and potentials for misinterpretation (Habyarimana et al. 2007; Desmet et al. 2012). Accordingly, complaints about neighbors, our central outcome variable, might not increase because (in-migrating) out-groups are perceived as threatening, but because general community erosion and disorganization in heterogeneous settings increase incivilities and disorder. This alternative explanation is considered prominently as part of our empirical analysis.

The Contested Boundaries Hypothesis

The evidence regarding community erosion and conflict in diverse or polarized settings is by no means conclusive (for reviews see Schaeffer 2014, p. 12ff.; van der Meer and Tolsma 2014). A number of recent studies try to overcome the inconclusive findings by focusing on the conditions under which an out-group is perceived as threatening. For the study of anti-immigrant sentiments, Hopkins (2010) proposes the politicized places hypothesis, according to which one such condition are sudden increases in the out-group population coupled with negative media reports. Legewie (2013) makes a related argument focusing on the effect of large-scale events such as terrorist attacks on anti-immigrant sentiments. Here we propose the contested boundary hypothesis and argue that neighborhood conflict is particularly likely to occur at fuzzy edges between ethnically homogeneous areas populated by persons of different ethno-racial groups. We claim that mixed areas that are sandwiched between homogeneous areas composed of different ethno-racial groups are more contentious than those characterized by ethno-racial heterogeneity, polarization, or out-group in-migration, per se. This argument extends the approaches discussed above by taking the local socio-spatial structure into account, beyond the previous focus on neighborhoods as isolated islands.

Boundaries have emerged as a key concept in sociological theorizing, particularly in research on ethnicity (Lamont and Molnar 2002; Wimmer 2008). Residential segregation, a seminal topic of neighborhood research, in many ways manifests and reinforces the categorical distinctions that lie at the core of the boundary argument (Massey and Denton 1998; Sampson 2012). Indeed, Campbell et al. (2009) argue that residential ethno-racial compositions play a decisive role in how people define their neighborhood's boundaries. Research on segregation, however, does not address what happens at places where groups border. Few studies examine such socio-geographical boundaries and their consequences for social life (Logan 2012; Spielman and Logan 2013; Grannis 2009).[1] Research on gang violence highlights that shared turf boundaries (Papachristos et al. 2013) or boundary crossings (Radil et al. 2010) are an important predictor of violence. Desmond and Valdez (2013) claim that neighborhoods at the edges of segregated black communities have particularly high frequencies of nuisance property citations, because non-black residents feel threatened by their black neighbors. Building on these ideas, we seek to explicate the conflict-generating mechanisms working at such socio-geographical boundaries between ethno-racial groups. Our argument about contested boundaries consists of two parts: First, the different

[1] Other research focuses on spatial inequality. Pattillo (2013, 2005), for example, identifies the black middle class' positioning at the boundaries between the advantages of white middle-class communities and the perils of poor black neighborhoods as a core determinant of their specific opportunities and disadvantages.

mechanisms emphasized by intergroup competition and defended neighborhood theory come together and work in concert at boundaries. Second, fuzzy boundaries are more contentious than well-defined ones.

At boundaries between homogeneous neighborhoods several mechanisms proposed by the different branches of intergroup competition and defended neighborhood theory jointly produce ethno-racial tensions. As reviewed above, a common argument in the literature is that ethno-racial compositions have the potential to stir social tensions, because out-group members are perceived as threatening. The defended neighborhoods literature further suggests that residents of ethnically homogeneous areas develop exclusive community identities. Campbell et al. (2009) note how ethno-racial compositions inform people's subjective construction of neighborhood boundaries correspondingly. Minorities' in-migration to homogeneous areas contests these subjective boundaries and is consequently met by strong resistance to defend the integrity of the dominant group's neighborhood community. Gould (2003) and others claim that polarized situations where two equally sized opponents face each other are even more contentious than circumstances where a majority defends its space against the in-migration of minorities. Here the ambiguity about social rank—i.e. who is the dominating group—breeds conflict. We maintain that the mechanisms discussed by the different approaches come together and work in concert at socio-geographical boundaries between two groups: the presence of the other group is salient (group threat), the situation is highly polarized (ambiguity about social rank), and exclusive ethno-racial community identities coupled with claims about group turfs are more pronounced than they would be in conventionally mixed areas (defended neighborhoods). Together, these mechanisms result in neighborhood conflicts at contested boundaries above and beyond those generally found in mixed neighborhoods.

Second, this joint effect of mechanisms, which were individually identified by different traditions, is particularly pronounced at poorly defined or *fuzzy boundaries*. Sharp or well-defined boundaries do not threaten the integrity of neighborhood communities. Such overt transitions between areas clearly define each group's turf (Campbell et al. 2009) and hence prevent ambiguities about social rank and group turfs. In other words, well-defined boundaries manifest where each group dominates and leave no interstitial space between the groups that could be the object of rivaling claims.[2] Fuzzy boundaries, by contrast, are characterized by such interstitial space.[3]. These transitional areas are ambiguously located between the homogeneous areas inhabited by two different groups and the members of the two groups mix. One might object that poorly defined boundaries simply identify ethno-racial heterogeneity insofar as members from the groups in adjacent homogeneous areas mix. From our perspective, this overlooks the importance of the ambivalent location between homogeneous areas composed of different ethno-racial groups. This location conjoins the conflict-breeding consequences of out-group salience, polarization, exclusive identities and group-turf entitlements that spill over from the adjacent homogeneous areas. In consequence, we predict that such areas are more contentious than diverse areas per se.

In summary, poorly defined boundaries between ethnically homogeneous areas of different ethno-racial groups are particularly prone to conflict. In these transitional areas several well-established conflict-generating mechanisms work in concert. This argument specifies the conditions under which diversity might erode community life and when it does not. It implies that neighborhood conflict does not necessarily arise from diversity per se but instead at poorly-defined boundaries that separate ethnic and racial groups. From this perspective, residential segregation and ethnic enclaves create contentious areas at the places where groups border. Based on this argument, we expect an inverse u-shaped relation between edge intensity and neighborhood conflict; where *edge intensity* is a spatial feature ranging from absent—no boundary, e.g. within an homogeneous neighborhood—to well-defined separation of two groups

[2]Lim et al. (2007) make a related argument about well-defined boundaries and present supporting evidence about violent conflicts in India and former Yugoslavia. Their argument focuses on "patches consisting of islands or peninsulas of one type surrounded by populations of other types" (Lim et al. 2007, p. 1543). Our argument, however, focuses on any boundary that separates groups in different neighborhoods. A clearly encircled island, for example, would be prone to conflict in Lim et al.'s approach but not in ours.

[3]The use of this concept follows classical disorganization theory for which interstitial areas are deprived neighborhoods located at the boundaries between wealthy neighborhoods (Thrasher 2000, (1927)).

(see illustration in introduction).

Data and Methods

Our analyses are based on data from 4.7 million time and geo-coded 311 service requests from New York City in 2010 and 2014, combined with data on the census block and tract level from the Census and American Community Survey 5-year estimates. In our main analysis, we focus on 2010 (1.63 million requests) and later conduct additional analysis based on service requests from 2014. 311 service requests allow us to track complaints about neighbors such as "Loud Music" or "Illegal Parking" as indicators of everyday neighborhood conflict across time and space, while adjusting for the general propensity to use the 311 system based on other service requests. Using multilevel negative binomial regression, we model the number of complaints as a function of ethnic heterogeneity and polarization—the key predictors of intergroup competition, community erosion and disorganization theories—as well as edge intensity as the concept at the center of our argument. To identify edges between ethnically homogeneous areas we use edge detection algorithms from computer vision and image processing.

Edge Detection Algorithms: Detecting Boundaries between Ethnic Neighborhoods

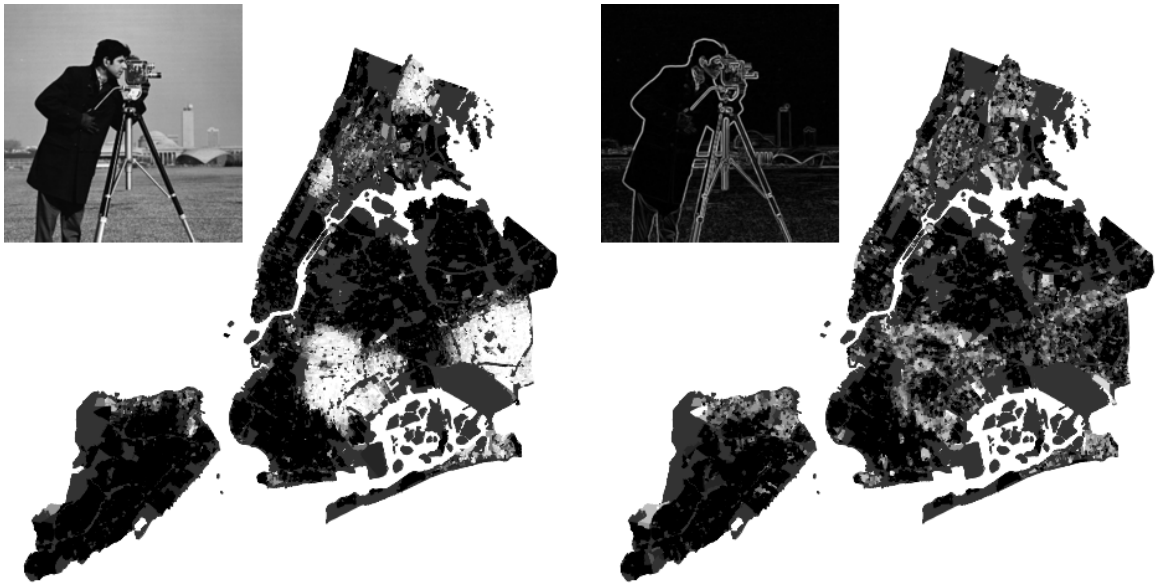
The term *edge detection* refers to a number of mathematical methods with the goal to detect "points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities" (Nosrati et al. 2013, p. 116; see also Ziou and Tabbone 1998; Shapiro and Stockman 2001). These algorithms are a fundamental and well-established tool in image processing and computer vision with applications ranging from image sharpening, over robotics, to driver-less cars (Shapiro and Stockman 2001). Edge detection algorithms are part of a larger literature on spatial boundary detection that includes various methods used in ecology, epidemiology and other areas, such as "wombling" (Dale and Fortin 2014; Jacquez et al. 2000) or methods based on ecocentric signatures and cluster analysis (Spielman and Logan 2013; Logan et al. 2011). Most of the existing boundary analysis methods are designed for either point-specific data with known coordinates or regular lattices such as images (Nosrati et al. 2013; Dale and Fortin 2014). [4] Directly applying these methods to the ethno-racial composition of neighborhoods would require a high resolution spatial grid with point-specific information about ethno-racial composition. The smallest available census aggregations, however, are on the census block level.

Legewie (2014) adopts and modifies edge-detection algorithms so that they can be applied to census block data. The main challenge is that commonly used edge detection algorithms are designed for image data in the form of regular grids. They ignore the different spatial extent of areas and their irregular spatial arrangement. To address this problem, the modified algorithm moves from discrete kernels commonly used in edge detection algorithms for images to continuous kernels that account for the irregular spacing of areas. While using continuous kernels to approximate a spatially discrete phenomenon (e.e. census blocks) has limitations as well, the algorithm is one of the only approaches that is applicable to contemporary census data. Appendix A gives a technical description of the algorithm and Legewie (2014) includes a comparison with (Bayesian) areal wombling.

The modified edge detection algorithms allows us to detect neighborhood boundaries as interstitial or transitional zones that fall between homogeneous areas populated by different groups. Hence our approach directly captures the core concept of our contested boundaries hypothesis. Importantly, our algorithm first calculates the edge intensity for each ethno-racial group separately. We then combine the information about the four ethno-racial groups' residential boundaries into one measure of edge intensity that indicates boundaries between *two* ethno-racially homogeneous

[4] An exception is (Bayesian) areal wombling for irregularly shaped geographic regions such as census tracts (Lu and Carlin 2005). Areal wombling essentially estimates the difference between all pairs of adjacent regions irrespective of the local spatial structure. This limitation makes it impossible to detect interstitial or transitional areas *located between two different groups*, which are at the core of our theoretical argument.

Figure 2: Illustration of Edge Detection Algorithm



Note: Edge detection algorithm applied to the proportion of black residents in each census block in New York City with inset of gray-scale image.

areas. In particular, we multiply the values for the two groups with the highest edge intensity. As a consequences, changes in racial composition from one dominant group to a mixed neighborhood or between differently composed mixed areas get assigned lower values whereas transitions between two ethnically homogeneous areas get assigned higher values (for a concrete example see Appendix A). Low values indicate no change in ethno-racial composition. This is the case both in ethno-racially homogeneous and in diverse areas as long as the composition remains unchanged. High values indicate abrupt changes from one ethno-racial group to another such as transitions from a black to a Hispanic area.

Figure 1 and 2 illustrate the result. Figure 2 shows both a popular edge detection algorithm applied to an image (small inset) and our modified algorithm applied to the proportion of black citizens in each census block in New York City (main figure). On the left, the figure (and image) first shows the input data with lighter shadings indicating a higher proportion of black citizens. On the right, it shows the output from the edge detection algorithm, highlighting the borders between areas with a high and low proportion of black residents. Figure 1 provides a more detailed view of Crown

Heights South in central Brooklyn (see Introduction for a detailed description).

Across the 29,655 inhabited census blocks in New York City, the average edge intensity is 0.08 with a standard deviation of 0.073. By definition, fuzzy edges are also ethno-racially mixed. But our edge intensity measure is theoretically (see arguments above) and empirically distinct from heterogeneity (the correlation is 0.25).

Estimation Strategy

In the following analyses, we use the number of complaints about neighbors on the census block level as the dependent variable and edge intensity as the main independent variable. Standard linear regression models are inappropriate to model such count data confined to positive integers. Poisson regression is one alternative, but the underlying distribution assumes that mean and variance are equal (Gelman and Hill 2007, p. 114). We therefore model the number of complaints using negative binomial regression, which allows for excess variability (over-dispersion) among the complaint calls (Gelman and Hill 2007, p. 115; Long and Freeze 2005, Ch. 8).[5] To account for the clustering of census blocks in tracts (many control variables are measured on the census tract level), we use multilevel negative binomial regression (Rabe-Hesketh and Skrondal 2008, Ch. 9). Formally, the model can be expressed as:

$$\lambda_{ij} = exp\left(\alpha + \delta D_{ij} + \varphi D_{ij}^2 + \mathbf{X}_{ij}\beta_1 + \mathbf{U}_j\beta_2 + \zeta_j\right)$$

where i and j are indices for census block and tract respectively. The term $\delta D_{ij} + \varphi D_{ij}^2$ models a quadratic relation between edge intensity and the number of complaints about neighbors λ_{ij}, evaluating our argument about an inverse u-shaped relationship. $\mathbf{X}_{ij}$ and $\mathbf{U}_j$ represent matrices of control variables on the census block and tract level, and the two β's vectors of corresponding coefficients. ζ_j is a random intercept that

[5]Another concern with count data are inflated zero counts (Gelman and Hill 2007, p. 126). Zero-inflated models are designed to address this problem. They are based on a binary model to predicts structural zeros and a count model to predict the counts. But there is no reason to believe that the number of 311 service requests is driven by two distinct processes, considering that our sample excludes census blocks where no one lives (see sample definition below).

captures unobserved heterogeneity between census tracts. In additional sensitivity analysis, we account for spatial autocorrelation using a spatial Bayesian hierarchical model, fit semi-parametric generalized additive models to allow for any functional relation between edge intensity and the number of 311 calls, and extend the model with census-tract fixed effects (see details in results section).

Geographic Regions and Coding of Variables

We construct our dataset from three sources: time and geo-coded 311 service requests from New York City, census block data from the 2010 Census Summary File 1, and census tract data from the 2010 American Community Survey 5-year estimates. Census blocks are the smallest geographic unit used by the Census Bureau. In NYC, a census block usually refers to a single city block. They sum up to a block group, which again make up a census tract. Overall, there are 38,792 census blocks with an average population of 210 residents embedded in 2,166 census tracts. We restrict our sample to all census blocks with at least one person and household and exclude public parks so that our final sample consists of 29,872 census blocks. Because of missing values on the predictor variables, the sample reduces to 29,632 census blocks nested in 2,106 census tracts (i.e. 0.8 and 1.1% missing values respectively).

Dependent variables and coding of 311 service requests Our dependent variable is based on 311 service requests from New York City. 311 is a centralized non-emergency telephone number, Internet platform, and smartphone app that allows city residents to file a request for or complain about issues as diverse as birth certificate services, fallen tree or branch removal, or broken heating. 311 was established in New York City in March 2003 to subsume more than forty separate agency help lines into one centralized service request system (Idicheria et al. 2012). It is operated around the clock on each day of the year and provides language translation services to over 180 languages. Today, the system handles over two million service requests per year. When a person files a service request such as reporting a noisy neighbor through the

311 service hotline, website or smartphone app, the person specifies the topic (e.g. “Noise Residential” featured prominently on the website and as an example on the hotline), provides further details based on a list of categories (e.g. “Banging/Pounding”, “Loud Music/Party”, “Loud Talking”, or “Loud Television”), and indicates the time and place. After filing a request, the information is forwarded to the appropriate city agency, such as the New York City Police Department, which responds to the complaint.

Previous research has used 311 data to capture community engagement (Lerman and Weaver 2014), political participation (Levine and Gershenson 2014), and physical disorder (O’Brien et al. 2015). We focus on neighborhood conflict indicated by complaints about neighbors. As outlined by Minkoff (2015), 311 service requests are determined by two factors: “conditions” such as physical disorder or neighborhood conflict, and “contacting propensity” as the general tendency to use the 311 system. Our measure is based on calls that capture “conflict between neighbors” as a condition and adjusts for the contacting propensity by controlling for other, unrelated service requests. Complaints about neighbors might not all be observed incidents of neighborhood conflict, but they are an interesting indicator of neighborhood life. They indicate tensions and conflicts that are not resolved in a neighborly way by knocking on someones door. Instead, residents reach out to the city as an external authority. Typical examples are complaint type “Noise” and its associated description “Loud Music”, or complaint type “Blocked Driveway” and its associated description “No Access”. Appendix B describes our coding scheme and procedure in detail.

311 complaint calls about neighbors do not refer to rare events such as hate crimes (Lyons 2007) or gang-related violence (Radil et al. 2010), but to more subtle forms of conflict that are a defining aspect of everyday life and have largely escaped quantitative research so far. In contrast to survey research, such behavioral measures are less affected by social desirability bias. Nonetheless, 311 service requests lack information on the identity of the caller, which is an important limitations that is further discussed in the results section and conclusion.

Block-level covariates Just as the number of complaint calls, the crucial independent variables are measured on the census block level. They rely on data from the 2010 Census. Edge intensity, which we use to evaluate our main argument, is based on ethno-racial shares for census blocks (for details see section on edge detection algorithms and Appendix A). The two indices for ethno-racial heterogeneity and polarization use the same data on ethno-racial shares. Following the convention in the literature, we use the Hirschman-Herfindahl Index (HHI) (Hirschman 1964) and the index of Ethnic Polarization (EP) (Montalvo and Reynal-Querol 2005).[6] These indices allow us to examine the conventional approaches in the literature.

Our models include a number of control variables on the census block level. Most importantly, we adjust for the general propensity to call 311 using the number of service requests that are clearly unrelated to neighborhood conflict (see coding above). This variable adjusts for what Minkoff (2015) calls "contacting propensity". The other variables on the census block level are the population size (in hundreds), the block's area-size, the proportion of the area that is covered by public housing, and the ethno-racial composition in terms of the proportion of black, Hispanic, and Asian citizens. In supplementary analysis, we consider population as an offset to account for differences in exposure insofar as the number of potential callers varies across areas (Gelman and Hill 2007, 111–113).

[6] Formally these indices are defined as

$$\text{HHI} = 1 - \sum_{i=1}^{I} s_i^2$$

$$\text{EP} = 1 - \sum_{i=1}^{I} \left(\frac{0.5 - s_i}{0.5} \right)^2 s_i$$

where s is the population share of group i and I is the number of groups in a given census block. In most situations, these indices are by design highly collinear (Schaeffer 2013a). Even in New York City where we observe the whole range of possible HHI and EP values, the correlation between the two indices is 0.91. In sensitivity analyses, we also explored the Theil Entropy Index—$E = \sum_{i=1}^{I} \pi_i \ln\left(\frac{1}{\pi_i}\right)$—as an alternative to the more commonly used HHI. The Theil Entropy Index relates nicely to our multigroup segregation index (see below) and only correlates with the index of ethnic polarization by 0.83. This alternative diversity index produces similar results.

Table 1: Description of Variables

Variables	Description
Dependent Variables	
Complaint calls, 2010	Number of complaints about neighbors (census block, 2010)
Complaint calls (noise)	Number of noise complaints about neighbors (census block, 2010)
Complaint calls (night)	Number of complaints about neighbors between 6 p.m. and 9 a.m. in 2014 (census block, 2014)
Block-Level Covariates	
Edge intensity	Measure of change in racial composition based on racial/ethnic counts for census blocks. The algorithm is discussed in the data and methods section and Appendix A.
Other 311 Service Requests	Number of service requests that are unrelated to neighborhood conflict as a measure for the general propensity to call 311.
Population size	Size of population in hundreds (also considered as exposure variable in sensitivity analysis)
Area-size	Size of area
Ethno-racial diversity	Hirschman-Herfindahl Index (HHI)
Ethno-racial polarization	Index of Ethnic Polarization (EP)
Public Housing	Proportion of census blocks that are NYC Housing Authority developments (public housing)
Racial composition	Proportion of black, Hispanic, and Asian citizens
Tract-Level Covariates	
Concentrated disadvantage	Index of six items (factor analysis):
	Poverty rate (factor loading: 0.79)
	Unemployment rate (factor loading: 0.56)
	Professional jobs (factor loading: -0.73)
	Share of high-school graduates (factor loading: -0.81)
	Share single mother families (factor loading: 0.75)
	Share of households that receive public assistance income (factor loading: 0.78)
Residential instability	Index of 3 items (factor analysis):
	Percentage of renter-occupied units (factor loading: 0.65)
	Share of residents who moved to another dwelling since 2005 (factor loading: 0.61)
	Housing unit rental vacancy rate (factor loading: 0.59)
Crime-prone population	Share of 15 to 34 year old males
Immigrant concentration	Index of three items (factor analysis):
	Share of foreign born residents (factor loading: 0.65)
	Share of residents who speak English less than "very well" (factor loading: 0.99)
	Share of Spanish speaking residents (factor loading: 0.52)
Foreclosures	Number of foreclosures in census tract
Multigroup segregation	Information theory index (Reardon and Firebaugh 2002) based on census 2010 block data on the population shares of ethno-racial groups (census tract level)

Tract-level covariates The other control variables are measured on the census tract level and based on the 2006-2010 American Community Survey 5-year estimates. They include a number of well-established predictors of neighborhood conflict (Sampson et al. 2002; Lyons et al. 2013): an index of concentrated disadvantage, residential instability, share of crime and conflict prone population, immigrant concentration, and the number of foreclosures in a census tract.[7] For all indexed control variables, we used the predicted factor scores based on an exploratory maximum likelihood factor analysis. Table 1 reports details on the items from which the indexed control variables are constructed and their factor loadings. Finally, we control for a multigroup segregation index[8] to clearly separate the concentration of groups from the boundaries between their communities. This index relies on the census 2010 block data on the population shares of ethno-racial groups but as a segregation index sums up to the census tract level. For the analysis, we z-standardize all variables with the exception of the number of other calls and our main explanatory variable, edge intensity.

Results

Our contested boundary hypothesis suggests that neighborhood conflict is more pronounced at fuzzy boundaries between ethnically homogeneous areas so that we expect an inverse u-shaped relation between edge intensity and neighborhood conflict. To evaluate this argument, we begin our analysis with a set of four multilevel negative binomial regressions predicting the number of 311 complaint calls about neighbors on the census block level in 2010. Table 2 shows the results. The models include

[7]The foreclosure data are from NYU's Furman Center: `www.furmancenter.org`

[8]We follow Reardon and Firebaugh's (2002) suggestion and estimate the information theory index:

$$H = \frac{1}{E}\sum_{i=1}^{I}\pi_i\sum_{k=1}^{K}\frac{t_k}{T}r_{ki}\ln r_{ki}$$

where E is Theil's Entropy Index (see above). π is the proportion and t the absolute number of group i in census block k. This segregation index "can be interpreted as one minus the ratio of the average within-unit population diversity to the diversity of the total population" (Reardon and Firebaugh 2002, p. 42).

edge intensity together with a quadratic term that captures the expected non-linear relation. Model I first shows a base-line set up. It includes population size, census block area-size, fixed effects for the five boroughs and the number of other service requests, which captures the general propensity of the population in a certain area to request services.

The results show a highly significant and positive coefficient for edge intensity and a negative one for the squared term. Figure 3 (dashed line) illustrates the curve-linear pattern implicated in these estimates. It shows the predicted number of complaints about neighbors (y-axis) as a function of our continuous edge intensity scale (x-axis). The figure reveals the expected inverse u-shaped relation. The empirical results suggest that the number of complaints initially increase until a maximum is reached at 0.36 edge intensity, followed by a gradual decline. At the maximum, the predicted number of complaints is 46% higher compared to areas with low values of edge intensity, indicating that fuzzy boundaries between ethnically homogeneous areas play an important role for conflict between neighbors. The vertical black line demarcates the upper end of the empirically observed scale of edge intensity, i.e., the most clear cut socio-geographical boundaries observed in New York City (0.5% of the values are larger but sparsely distributed over the rest of the scale). Predictions above the demarcation extrapolate our model beyond the empirically supported range. They show our model's predictions for extremely well-defined edges between ethnically homogeneous groups as they might be observed in other cities such as Chicago or Detroit. Figure 1 in the introduction nicely illustrate the range of edge intensity values observed in NYC.

Model II expands the baseline set up by a set of commonly used neighborhood conflict predictors capturing different area-demographics. Population size[9], the share of crime prone males (aged 15 to 34), concentration of immigrants, residential instability, and the number of foreclosures are themselves positive predictors of neighbor

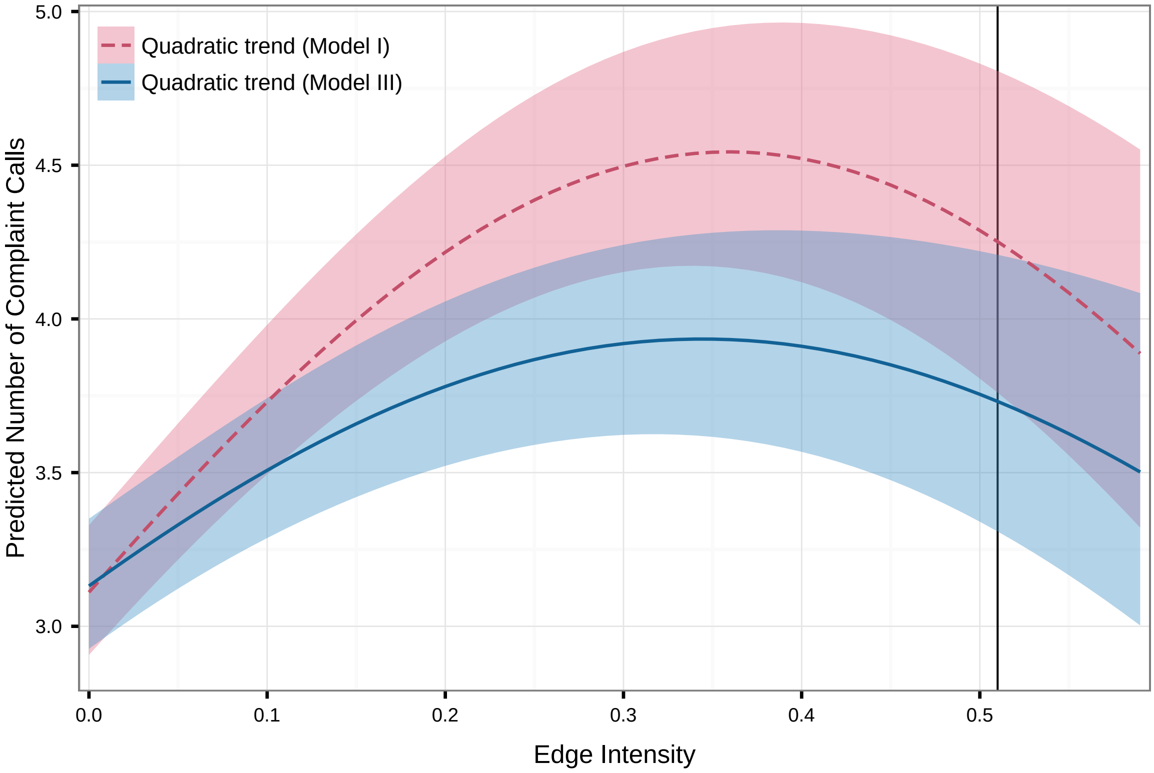
[9] In separate model specifications, we use population size as an exposure or offset variable. This alternative specification fixes the coefficient for logged population to 1 and interprets the number of complaints relative to the number of potential callers (population size) as the baseline or "exposure" (Gelman and Hill 2007, 111–113). The findings show the same pattern as the ones reported here.

Table 2: Effect of Edge Intensity on Number of Complaint Calls

	Model I	Model II	Model III	Model IV	Model V
Edge intensity	2.108***	1.936***	1.327***	1.345***	1.621***
	(0.190)	(0.184)	(0.186)	(0.187)	(0.205)
Edge intensity (squared)	−2.932***	−2.713***	−1.928***	−1.939***	−1.893***
	(0.393)	(0.380)	(0.383)	(0.384)	(0.421)
Control variables					
Population (in 100s)	0.088***	0.093***	0.090***	0.090***	0.091***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Area	0.079***	0.091***	0.090***	0.090***	0.099***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)
Other service requests	0.003***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Public housing		−0.093***	−0.097***	−0.100***	−0.096***
		(0.008)	(0.008)	(0.008)	(0.008)
Crime prone population		0.061***	0.050***	0.046***	0.041***
		(0.007)	(0.007)	(0.007)	(0.007)
Concentrated disadvantage		−0.103***	−0.090***	−0.131***	
		(0.014)	(0.014)	(0.016)	
Residential instability		0.184***	0.163***	0.160***	
		(0.014)	(0.014)	(0.014)	
Immigrant concentration		0.113***	0.102***	0.103***	
		(0.013)	(0.013)	(0.015)	
Foreclosures		0.045***	0.044***	0.032*	
		(0.013)	(0.013)	(0.013)	
Multigroup segregation (H)		−0.136***	−0.110***	−0.106***	
		(0.012)	(0.012)	(0.012)	
Ethnic polarization (EP)			−0.081***	−0.088***	−0.083***
			(0.018)	(0.018)	(0.018)
Ethnic diversity (HHI)			0.223***	0.222***	0.234***
			(0.018)	(0.018)	(0.019)
Proportion African-American				0.044**	0.074**
				(0.014)	(0.021)
Proportion Hispanic				0.069***	0.065***
				(0.012)	(0.013)
Proportion Asian				0.011	0.025
				(0.011)	(0.016)
Borough fixed effect	✓	✓	✓	✓	✓
Census tract fixed effect					✓
Constant	0.784***	0.754***	0.806***	0.779***	0.779***
	(0.036)	(0.035)	(0.035)	(0.036)	(0.036)

Note: N=29,632; Estimates based on multilevel negative-binomial regressions.
*p < 0.05, ** p < 0.01, *** p < 0.001; standard errors in parenthesis*

Figure 3: Number of Complaint Calls by Edge Intensity



Note: The figure shows the predicted number of complaint calls as a function of edge intensity based on the quadratic specification from Model I (dashed line) and Model III (solid line) in Table 2. The vertical line indicates the empirically observed range for edge intensity in New York City.

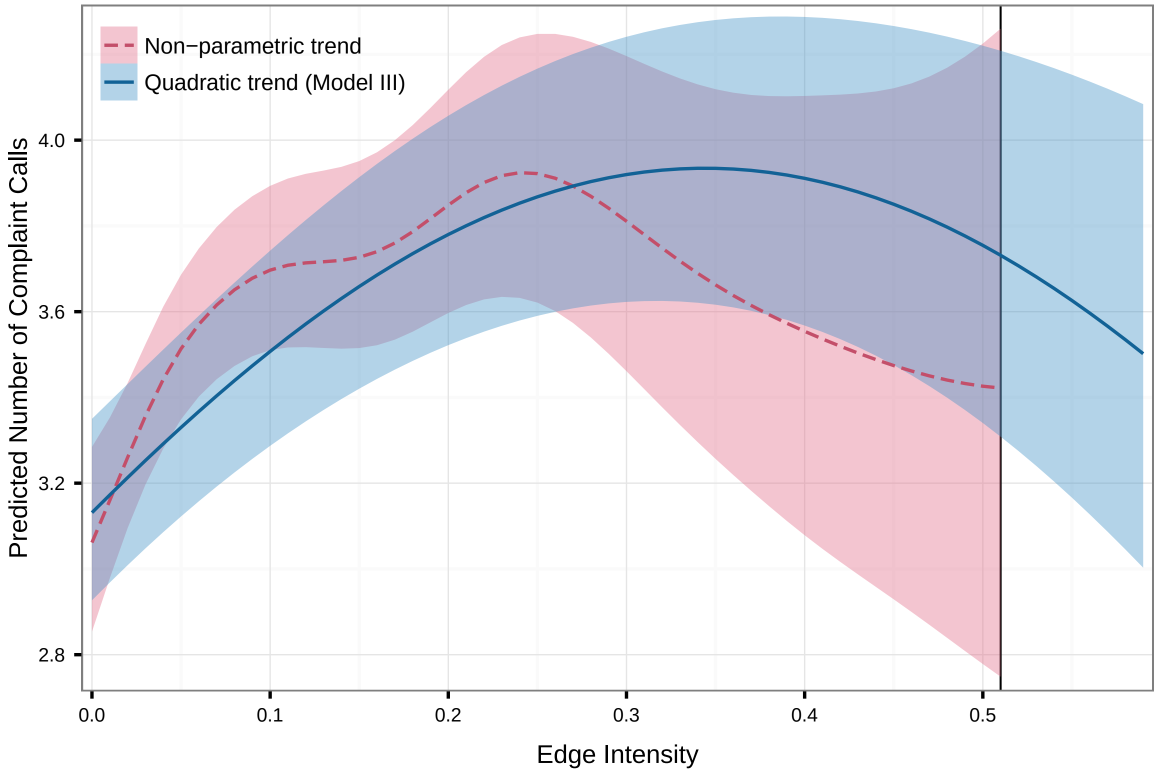
complaints. Concentrated disadvantage, the share of a census block covered by public housing, and multi-group segregation, however, reduce the number of complaints throughout all estimated models. This pattern is in line with the argument that citizens in disadvantaged communities are less likely to contact a city agency. Overall, these estimates are intuitive and validate the coded complaint calls as indicators of neighborhood conflict. Their introduction to the model does not diminish the role of edge intensity.

Model III adds ethnic polarization and heterogeneity and Model IV the full set of ethno-racial population shares. Irrespective of the particular specification, the pattern observed in the first model remains stable. The results continue to show a robust curve linear relation between edge intensity and the number of complaint calls about neighbors. The pattern persists even in Model V with census tract fixed effects, so that the estimates are confined to *within* census tract variations. The only considerable decrease in edge intensity's explanatory power is caused by the introduction of the two ethno-racial composition indices in Model III. In line with scholars who argue that communication problems, sparse networks and declines in social control generally erode community life in ethnically diverse settings, our results show that the number of complaint calls increases with the level of ethnic heterogeneity. The reduction in the effect of edge intensity is not surprising. By definition, diversity is higher at fuzzy boundaries and this diversity is associated with a higher number of complaint calls. Accordingly, diversity acts as a confounder so that controlling for the variable in Model III reduces the association with edge intensity. Nevertheless, the role of edge intensity remains substantial. The diversity-adjusted (solid line) and baseline (dashed line) patterns are both illustrated in Figure 3. They show the same curve-linear relation with a maximum around 0.35 and 0.36 respectively. Compared to the first model, the differences are less pronounced but still substantial with a 26% increase from areas surrounded by likewise census blocks to fuzzy boundaries at the maximum. Accordingly, the location between homogeneous communities further boosts the number of complaint calls beyond the obstacles of community erosion and disorganization generally found in mixed neighborhoods.

Our findings also speak to the established literature on ethnic diversity and polarization. Proponents of the community erosion literature find support in our result that ethno-racial diversity is systematically related to increases in neighborhood conflict calls. But there is no evidence for the predictions from intergroup competition theories about increased neighborhood conflict in polarized settings. According to Model III there are even significantly fewer complaint calls in polarized settings, which might be due to multicollinearity.[10]

[10]The variance inflation factor (VIF) values are 4.92 for polarization and 5.03 for diversity, which is generally considered as critical. Additional sensitivity analyses show that polarization positively predicts the number of complaint calls when diversity is excluded from the analysis. In support of the community erosion and disorganization literature, ethno-racial diversity turns out to be a more consistent predictor of complaint calls about neighbors. The size of the estimated coefficient is positive and larger both with and without polarization as an additional control variable.

Figure 4: Number of Complaint Calls by Edge Intensity



Note: The figure shows the predicted number of complaint calls as a function of edge intensity based on the quadratic specification from Model III in Table 2 (solid line) and a semi-parametric specification (dashed line). The semi-parametric specification uses generalized additive models and predicts the the number of complaint calls based on a semi-parametric term for edge intensity (x-axis) conditional on the same set of control variables.

Sensitivity Analyses

We conduct four sensitivity analyses that address various concerns about our data and modeling strategy. First, we evaluate the *validity of the quadratic specification*. This specification imposes a certain functional form that nicely captures our expectation about an inverse u-shaped relation but it may conceal a more complex association. To address this concern, Figure 4 compares the quadratic trend with the corresponding relation from a flexible, non-parametric specification.[11] We restrict the predictions to the observed range mainly because predictions above that value (indicated by the

[11]The figure is based on generalized additive models (Hastie and Tibshirani 1990). These models predict the number of complaint calls based on a smoothing spline for edge intensity (x-axis in the figure) conditional on the same set of control variables used for the quadratic specification in Model III in Table 2. This specification does not explicitly model the multilevel structure of the data (census blocks embedded in census tracts) but instead adjusts the standard errors for clustering on the census tract level.

vertical line) are extremely uncertain. The non-parametric trend presented in Figure 4 (dashed line) shows a similar curve-linear relation indicating that our quadratic specification closely resembles the actual association. Second, we test the *validity of our coding scheme* for the dependent variable by using two alternative definitions. The first alternative focuses noise complaints as a clear and unambiguous indicator of conflict between neighbors (see Table B1 for details on coding). The second alternative only uses service requests filed during the evening and in the morning (between 6 p.m. and 9 a.m.). This definition of the dependent variable alleviates concerns that people file 311 service requests at work or at other locations (note that O'Brien et al. 2015 find that most service are filed close to home).[12] The results for these two alternative definitions of the dependent variable are similar to our main analysis. Both for noise calls and night calls, they show an inverse u-shaped relation between edge intensity and the number of complain calls (see Table 3). Third, we examine whether our results are driven by *spatial autocorrelation*. In particular, we reestimate our main models using a spatial Bayesian hierarchical framework that accounts for autocorrelation.[13] The finding largely resemble the results presented here partly with slightly higher coefficient estimates for the main effects (see Table 3). Finally, we address concerns about the *reliability of edge intensity and control variables*, which might arise due to the "small number" problem. The variables are based on Census blocks and tracts with partially small populations. Small changes in the number of members from a certain group might translate to large compositional differences, which translate to high edge intensity values. In addition, the margin of error in the census-tract estimates from the American Community Survey are generally large (Spielman et al.

[12]The exact timing of service requests is only available after mid-2013. In particular, 311 service requests are processed by different city agencies and the agencies started to provide an exact time codes step-by-step. This sensitivity analysis focuses on data from 2014 because almost all agencies provided exact time codes by that time. The only important exception is the NYC Department of Housing Preservation and Development (HPD), which never started to include the time of requests. With about 36.7%, HPD service requests make up a significant proportion of all 311 calls and play an important role for our control variable "number of other calls".

[13]The model is based on a Bayesian intrinsic conditional autoregressive (CAR) regression (Beale et al. 2010). The adjacency matrix captures all adjacent neighbors with equal weighting. The model is estimated via integrated nested Laplace approximations (INLA) using the R-INLA software (Beguin et al. 2012). Different choices for prior distributions lead to similar results.

Table 3: Sensitivity Analysis

	Noise Calls 2010	Night Calls 2014	Bayesian CAR Model	Disorder & Civic Controls
Edge intensity	0.905**	1.249***	1.709***	1.211***
	(0.321)	(0.187)	(0.205)	(0.185)
Edge intensity (squared)	−1.536*	−1.879***	−2.303***	−1.816***
	(0.695)	(0.385)	(0.408)	(0.383)
Control variables	✓	✓	✓	✓

Note: N=29,631; Control variables based on Modell III in Table 2. The coefficients and standard errors for the Bayesian CAR Model are based on the mean and the standard deviation of the posterior distribution.
*p < 0.05, ** p < 0.01, *** p < 0.001; standard errors in parenthesis*

2014). To address this problem, we first create ten plausible values for each of our measures based on the sampling distribution of the estimates. In the next step, we propagate the error-rate to our final analyses by repeating the analysis for each set of plausible values. We then summarize the results based on Rubin's (1987) repeated imputation summary statistics. These estimates account for the predictors' error-rates and again reaffirm our conclusions (edge intensity: $\delta = 1.39, \mathrm{p} < 0.000$; squared term: $\varphi = -1.99, \mathrm{p} < 0.000$).

Alternative Explanation: Social Disorganization at Neighborhood Boundaries

Our findings show a clear curve-linear association between edge intensity and the number of complaint calls on the census block level. However, general community erosion and disorganization could alternatively account for the observed pattern (see discussion above). Fuzzy boundaries might lack the social control of the adjacent homogeneous areas, because neither group feels responsible or has the capacity to enforce social norms. In consequence, they might be characterized by disorder and incivilities. This problem is particularly pronounced because the 311 data lack information on the identity of the caller and the person s/he complains about so that the 311 data does not allow us to test the proposed mechanisms underlying the contested boundary hypothesis directly—a limitation of our data further discussed in the conclusion. The models presented in the last section, however, control for the most prominent structural conditions of community erosion and disorganization, namely concentrated disadvantage, residential instability, and ethno-racial diversity. In addition, we present two pieces of evidence, which suggest that community erosion and disorganization is an important complementary, but not a competing explanation.

First, we extend our regression models with additional control variables for physical disorder and pro-social civic action. The two concepts capture the mechanisms that are at the core of the general community erosion and disorganization literature. They are measured based on an extended coding of 311 service requests. First, we replicate O'Brien et al.'s (2015) measure of physical and social disorder. Their measure is based on Boston's 311 system (the "Constituent Relationship Management" (CRM) system) and tested for validity and reliability via neighborhood audits. While the data from New York City does not allow us to duplicate all aspects of their coding schema, we can replicate their measures of "Housing issues", "Graffiti", and "Trash". Housing issues are the most reliable indicator for physical disorder identified in their study. Second, the measure for civic action is based on 311 calls related to damaged trees as an instance of collective action or the residents' willingness to engage for community concerns. In particular, we count the number of 311 service requests related to damaged, broken or dead trees adjusting for the actual distribution of trees and their condition based on the New York City Street Tree Census conducted by the NYC Department of Parks & Recreation. The fourth column in Table 3 displays the results. The model replicates Model III from Table 2 with additional measures for physical disorder and civic action. The findings show that the observed relation between edge intensity and the number of complaint calls is reduced in strength, but remains substantial and significant.

Second, we collect additional data from Internet forums to examine the salience of race and ethnicity in complaints about neighbors. 311 data do not allow us to establish the role of race and ethnicity, because there are no information on identities of callers or the person they complain about. Our systematic search for open-ended complaints about neighbors in the Internet forum of the website city-data.com allows us to ensure that ethno-racial conflict is a common topic in complaints about neighbors.[14] Our search concentrated on the local forum for "New York City" and was based on the keywords "noise" and "neighbor". It resulted in 109 threads containing 4,474 written comments. Most posts are simple approvals and rejections, advice and suggestions, or questions and inquiries. 803 comments (roughly 18%), include open-ended complaints about neighbors (coded in line with our definition of 311 neighbor complaint calls). This data source, of course, is problematic in many ways such as the well-documented bias in online activity (Golder and Macy 2014). It does, however, capture common themes in complaints about neighbors, often in direct relation to the 311 system in New York City . To examine the salience of ethnicity and race in these open-ended complaints, we coded each complaint for references to any social group such as social class, ethnicity and race, age, drug and alcohol abuse, or family status. This strategy allows us to investigate how frequent ethnic categorizations are among those complaints that actually include a group reference (for a similar approach to survey research see Schaeffer 2013b).

Out of all open-ended complaints, 57% entail a group reference (e.g. drug addicts or teenagers). Among these, race and ethnicity is by far the most common type of categorization invoked in complaints about neighbors. 257 complaints (56%) *explicitly* mention the racial or ethnic background of the accused culprit(s). The next common categories are persons of low socio-economic status (35%) and children/teenagers (13%).[15]

Aside from explicit racial and ethnic references, there are ambiguous and potentially *implicit* ethno-racial categorizations. Particularly posts about socio-economically

[14] City-Data is a popular Internet forum that hosts discussions concerning US cities. As of April 2014, the website had 20 million unique visitors per month with more than 23 million posts and over 1.3 million registered members.

[15] A small number of users frequently repeat their complaints within the same thread, we recalculate our statistic as the proportion of users per threat who frame at least one of their complaints in ethno-racial terms. The adjusted statistic is even higher with 59% of users per threat making at least one ethno-racial reference in their complaints.

disadvantaged groups often include implicit ethno-racial associations, for instance:

> I grew up ghetto, i was hood for the first 20yrs of my life [...] Whenever i see people in my old hood that i grew up with still doing the same **** and even younger people in the area call me a 'WHITETINO'. (user: silverbullnyc, 22 March 2014, 08:43 PM)

Other posts have less obvious ethno-racial connotations such as "ghetto people", "hood rats", or "hood riff raff", as exemplified by this post from the same thread:

> We are complaining about the classless GHETTO mofos that 'chill' hard in groups that make their presence known. Usually obnoxious teenagers and young to mid adults. However I've seen grown ass men in their 40s and 50s act the same way and guess what the common denominator is??????? They ALL come from a 'hood' background and subscribe to THAT culture. (user: hilltopjay, 05 March 2014, 03:46 PM)

Posts with such implicit ethno-racial categorizations make up another 16% of the complaints blaming specific groups. Accordingly, between 56 and 70% of all complaints that refer to a particular group suggest that the conflict has a ethno-racial dimension. This finding does not overcome the limitations of our data, but it validates the relevance of ethno-racial conflicts for complaints about neighbors.

Conclusion

Over the last decades, Western societies have experienced a permanent rise in cultural, religious and racial diversity. Despite the welcomed enrichment, this demographic shift has sparked a debate about eroding social trust and neighborhood conflict among scholars, policy makers and pundits alike. Previous research has largely focused on ethno-racial diversity and polarization within pre-defined spatial units as the culprits of social tensions and withdrawal from public neighborhood life. But evidence on generic diversity effects is mixed. In this article, we proposed the contested boundary hypothesis as a refined contextual explanation of neighborhood conflict that takes a city's local spatial structures into account. Combining different branches of intergroup competition theory, we argue that neighborhood conflict arises not from mere polarization or mixing, but at fuzzy boundaries defined as edges between ethnically homogeneous areas that are poorly defined. Well-defined boundaries with overt transitions from one group's turf to another's prevent conflict as they are accepted divisions between groups. At fuzzy boundaries, however, several processes come together. The polarized arrangement of two homogeneous groups with exclusive identities results in ambiguities about group rank and exclusive entitlement claims spilling over from the adjacent group turfs. For this reason, poorly defined boundaries sandwiched between ethnically homogeneous areas are more prone to conflict than mixed neighborhoods per se. This argument highlights how residential segregation creates contentious areas at the places where groups border.

To evaluate our argument, we applied edge detection algorithms from computer vision and image processing to census block and tract data. Based on 4.7 million 311 service requests from New York City, a series of analyses consistently show an inverse u-shaped relation between edge intensity and the frequency of complaint calls. In particular, the number of complaint calls increases by 26% as we move from areas surrounded by similar neighborhoods to those that lie within fuzzy edges between ethnically homogeneous areas. Subsequently the effect gradually declines as the edges become well-defined. These analyses account for all common measures in the neighborhood literature indicating that racial and ethnic boundaries are related to neighborhood conflict above and beyond established measures in the literature. Nonetheless, the findings are limited by the observational nature of the data, which makes it difficult to establish causality (Morgan and Winship 2014; Legewie 2012), an important topic for future work on contested boundaries.

Our contested boundary hypothesis is a theoretical contribution to intergroup-conflict theory and neighborhood research more broadly. It refines the generic prediction about conflict and tension in polarized settings by emphasizing the role of cities' overall socio-spatial structures. This approach overcomes the "aspatial" treatment of neighborhoods or regions as isolated contextual units. Instead our research contextualizes a well-known context effect, insofar as we show that even contextual effects depend upon the wider socio-geographical structure they are embedded in. Our argument helps us to understand both the conditions under which out-groups are perceived as threatening and the conditions under which ethno-racial mixing is peaceful, namely in city's integrated areas without any ethnic enclaves based on exclusive identities.

Our application of edge detection algorithms allows us to identify socio-geographical boundaries between homogeneous areas. In addition to advancing geographical boundaries as a theoretical concept to the neighborhood literature, we are the first to apply a corresponding measurement tool based on edge detection algorithms. In contrast to previous neighborhood research, the resulting socio-geographical boundaries are features of the city's local spatial structures. They stand in sharp contrast to the common "aspatial" treatment of neighborhoods or regions as random, independently sampled contextual units. This methodological innovation allows researchers to study how socio-geographical boundaries and interstitial zones of different types shape further aspects of social life. The importance of residential segregation is well established and we believe that socio-geographical boundaries complement the role of residential segregation in many regards. Here we have focused on ethno-racial boundaries, but we are certain that other types of socio-geographical boundaries, such as socio-economic, political or religious boundaries also shape important dimensions of social life. We hope that future research will apply and advance the tools proposed here, and examine the conditions under which edge intensity has an influence on various outcomes.

Our analyses make use of the unique opportunity to work with process-generated data from 4.7 million time and geo-coded 311 service requests from New York City. We use these data to track neighborhood conflicts as indicated by complaints about neighbors across time and space. Over the last years scholars have become more and more enthusiastic about the potentials of so called "big data" and 311 service requests in particular. With millions of analyzed calls, our article is an example of how sociologists can study socially relevant real life actions of citizens using such data. But our study also shows potential limitations of process-generated data and why such analyses need to be complemented by survey and qualitative research. In our case, the trade-off is that the proposed mechanism remains untested on the micro-level. We have no information about the callers' underlying motives and we are unable to distinguish between intergroup and intragroup conflict. Instead, our analysis is purely ecological. We do not face the "fallacy of ecological inference", which warns against confusing aggregate with individual level correlations, as both our dependent variable and proposed explanation are contextual. Nevertheless, residents' perceptions of threat and motives to defend their neighborhood that underlie our contested boundary hypothesis remain unobserved and should be the subject of future research. We conclude by encouraging scholars to advance our knowledge on the social significance of socio-geographical boundaries.

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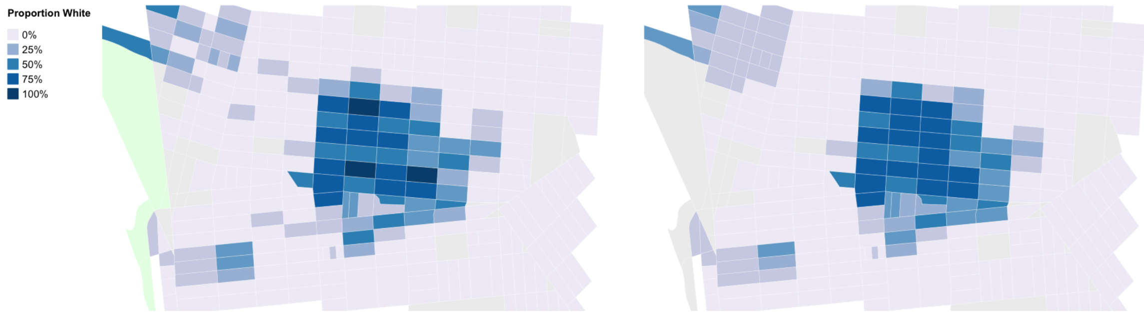
Appendix A Edge Detection Algorithms

Over the last decades, researchers have developed a range of different methods to detect boundaries (Dale and Fortin 2014; Jacquez et al. 2000; Spielman and Logan 2013; Logan et al. 2011). Most methods focus on point-specific data with known coordinates that are spaced regularly (lattice or grid) or irregularly. An exception is (Bayesian) areal wombling for irregular shaped geographic regions such as census tracts (Lu and Carlin 2005). Areal wombling essentially estimates the difference between all pairs of adjacent regions irrespective of the local spatial structure and geographical scale. The design of the approach makes it impossible to detect interstitial or transitional areas located between two groups, which are a key part of our theoretical argument. Following Legewie (2014), we instead use *areal edge detection* as a modified edge detection algorithms. The term *edge detection* refers to a number of mathematical methods with the goal to detect "points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities" (Nosrati et al. 2013, p. 116; see also Ziou and Tabbone 1998; Shapiro and Stockman 2001). Existing edge detection algorithms are designed for image data, which are essentially defined as a matrix data structure representing a grid of pixels. Legewie (2014) adopts and modifies these methods so that they can be applied to irregular spatial units such as census block data as the smallest available census aggregations. In particular, the algorithm involves three steps and uses the proportion of white, black, Hispanic, and Asian residents in each census block as input data.

First, we apply an edge-preserving smoothing algorithm to each of our variables, i.e. the shares of the four groups. Smoothing is commonly used to remove noise from the image and a popular step before applying edge detection algorithms (Nosrati et al. 2013), or other boundary analysis methods (Lu and Carlin 2005). In our case, it helps us to clear our data from measurement errors. It reduces the influence of small variations in the racial composition of census blocks, which distract from the important edges we want to detect. The use of raw, un-smoothed data may identify artificial boundaries between two adjacent areas with small populations. In this context, small

Figure A1: Illustration of Smoothing for Crown Heights South, Brooklyn

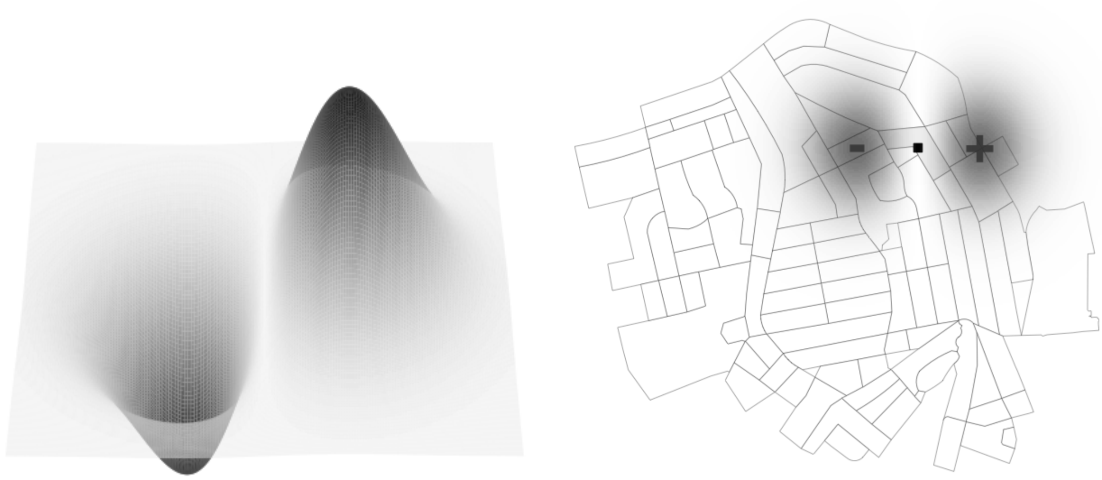


changes in population counts for each group can lead to extreme differences in population shares. The edge-preserving smoothing approach is based on a bilateral filter based on spatial distance and distance in the domain of the relevant covariate (Tomasi and Manduchi 1998).[16] Figure A1 illustrates the result with a detailed view of crown heights south in Brooklyn (raw data on left side and smoothed data on right side).

The second step of the algorithm measures edge intensity by identifying the places at which the composition of the population changes most rapidly. These compositional changes or discontinuities in a spatial attribute are detected by convolving the (discontinuous) spatial surface with an appropriate kernel. Convolution is a simple mathematical operation denoted by $\otimes$. The convolution is performed by "moving" the kernel over the spatial surface. The edge intensity for each area is calculated by placing the kernel above the centroid of that area (illustrated in Figure A2b) and then integrating the point-wise product of the kernel and spatial surface over the x- and y-dimensions for the domain of the kernel. The kernel is based on the first-derivatives of the multivariate normal distribution with a mean of zero and a 2×2 variance-covariance matrix with zero off-diagonals and a single variance parameter σ^2 for scaling in the diagonal (see Figure A2a). The spatial surface is discontinuities and defined by the areal data with the value at point (x, y) equal to the racial composition

[16] The extent of smoothing is determined by the variance parameter of the Gaussian function in both the spatial and the covariate domain. In our analyses, we use a standard deviation of 0.15 for the covariate domain (other values lead to similar results) and different parameters for the spatial Gaussian ranging from a standard deviation of 250 to 1000 feet (about 76 to 300 meter). The results presented here use 569.4 feet, which is the average distance between centroids of neighboring blocks. With this scale parameter, a block with an average distance to the focal block is weighted with a factor of 0.52 (normalized weights with 1 corresponding to zero distance for the focal block itself).

Figure A2: Areal Edge Detection



(a) Kernel in the x-direction (b) Kernel placed over areal unit

of the areal unit that contains the point (see Legewie 2014 for a formal description of the procedure). Without any compositional changes around the focal area, the left and right (or top and bottom) of the kernel balance each other out. When the composition of the population changes, however, the returned value is positive or negative.

The result is the gradient for each census block in the x-direction. The analogous gradient for the y-direction is based on a comparison of the area north and south to the focal block, not west and east as in Figure A2). The change in the two directions are combined to obtain the overall magnitude of change in the proportion of residents from a specific racial groups. The corresponding edge map for one of the four groups (blacks) is shown in Figure 2 for New York and in Figure 1 for a detailed view of crown heights in Brooklyn. This approach accounts for the irregular size, shape, and spacing of surrounding blocks by integrating over the entire non-zero domain of the kernel. Areas that are large and centrally located in the kernel domain receive higher weights compared to areas that are small or located at the margin of the kernel. The spatial scale parameter makes it possible to study boundaries at different geographical scale. The results presented here are based on a locally adaptive scale parameter that is defined as the average distance to the surrounding blocks (the average distance between blocks is 569.4).[17]

In the third and final step, we combine the information from the four racial groups into one measure of edge intensity. This operation resembles the combination of different color channels for edge detection of RGB images (Nadernejad et al. 2008, p. 1512). There are different ways to combine the edge maps. The goal of our approach is to identify edges between two ethnically homogeneous areas. To accomplish this goal, we simply multiply the values for the two groups with the highest edge intensity. As a consequences, changes in racial composition from one dominant group to a mixed neighborhood get assigned lower values whereas transitions between two ethnically homogeneous areas get higher values. As an example, consider the transition from a neighborhood that is entirely white (100%) to a mixed neighborhood with an equal share for each of the four groups. In this scenario, the proportion of white residents drops by 75% and the share of the other groups increases by 25%, which translates to an edge intensity of 0.75 for white and 0.25 for the other groups. Following our approach to combine the edge maps for the different racial groups, this scenario implies an overall edge intensity of 0.188. Now imagine that the white area changes to a predominantly black neighborhood with 75% black and 25% white residents. In this case, the edge intensity for white remains unchanged (75% drop in population share) but the edge intensity for blacks is 0.75 insofar as the proportion of black residents increases from 0 to 75%. This translates to an overall edge intensity of 0.56.[18] Accordingly, our approach to combine the edge maps of different racial groups highlights transitions between two ethnically homogeneous areas, which are at the center of our theoretical argument. The results are illustrated in Figure 1 with additional discussion in the main text of the article.

[17] For a constant standard deviation, the findings are consistent across a standard deviation of about 300 to 1200 feet. Smaller parameters essentially eliminate all boundaries because in most cases the entire kernel domain falls into an area. Future research should explore the role of spacial scale for neighborhood boundaries.

[18] Note that this fabricated example illustrates the point but does not reflect the complexity of our algorithms based on smoothing and continuous kernels. The arbitrary values used in this example can therefore not be compared to the scale of our actual edge intensity variable.

Appendix B Coding of Service Requests

For the coding of a service request as complaint about neighbors, we rely on the classification and brief standard description that are part of each 311 service request. In particular, the 4.7 million 311 service requests from 2010 and 2014 are classified into 1,386 complaint-type/description combinations. Our analysis focuses on complaint calls that indicate neighborhood conflict, which we operationalize as complaints about the behavior of particular persons or a group of people. Typical examples are complaint type "Noise" and its associated description "Loud Music", or complaint type "Blocked Driveway" and its associated description "No Access". Table B1 discusses some of the most common service requests in 2010 coded as complaints about neighbors. The coding excludes complaints about disorderly conditions such as "Graffiti" or "Condition Attracting Rodents", which have been the focus of previous studies (O'Brien et al. 2015; Boggess and Maskaly 2014). Such signs of physical disorder could indicate that residents take care of their neighborhood, which contradicts our intention to measure neighborhood conflict. As a second variable, we also code service requests that are unrelated to neighborhood conflict, such as "Sewer Catch Basin Clogged/Flooded" or "Snow, Icy Sidewalk" (Table B1 provides further typical examples). Other service requests allow us to control for the "contacting propensity" as the general tendency to use the 311 system. Residents of disadvantaged communities, for example, might hesitate to contact authorities. The validity of our indicator for neighborhood conflict can be evaluated empirically, by looking at its associations with well-established neighborhood conflict predictors. As discussed in the results section, these associations indeed cross-validate our measure.

For the actual coding, the 1,386 complaint types were sorted by frequency. The first 300 comprise 95.7% of all calls and were coded individually by both authors. Difficult cases were flagged and discussed in multiple meetings, which allowed us to develop a consensus. For all flagged cases, both authors justified their coding decision and quickly came to an agreement considering that the coding scheme is relatively simple. The other 1,086 call types (4.3% of all calls) were coded by a trained research

Table B1: Coding of typical 311 service requests

Category	% Conflict/ Other Calls	% All Calls	Description
Typical Complaint Call About Neighbor			
Noise complaints	29.0%	2.6%	A number of categories (23) refer to noise complaints about neighbors including “Noise - Street/Sidewalk: Loud Music/Party”, “Noise: Loud Music/Nighttime”, “Noise - Park: Loud Music/Party”, or “Noise: Neighbor”. Excluded from this coding are commercial noise complaints such as “Noise - Commercial: Loud Music” or complaints about noise from construction or helicopters. In sensitivity analysis, we replicate our finding based on noise complaints exclusively, with largely similar results.
Blocked driveway	28.7%	2.5%	The categories “Blocked Driveway: No Access” and “Blocked Driveway: Partial Access” are two of the most frequent service request coded as neighborhood conflict. Importantly, these categories are distinct from other “Blocked Driveway” requests related to fallen tree branches or construction.
Illegal conversion of residential building/space	2.7%	0.2%	The category “Illegal Conversion Of Residential Building/Space” includes the (potentially illegal) short-term renting of private living space through Airbnb or similar websites and again is distinct from other categories that refer to commercial activities.
Typical Other Service Requests			
Heat	17.7%	13.0%	The most common service request unrelated to neighborhood conflict refers to inadequate heating.
Plumbing	9.3%	6.8%	A number of service requests that are unrelated to neighborhood conflict refer to pluming issues such as “Water-Leaks”, “Water-Supply”, “Basin/Sink”, or “Bathtub”.
Paint - plaster	7.8%	5.7%	A number of service requests that are unrelated to neighborhood conflict refer to paint or plaster conditions at “Ceiling”, “Walls”, “Window/Frame”, “Doors/Frame”, or “Radiator”.

Note: $N = 147{,}828$ *neighbor complaint calls; 1,630,955 service requests in 2010.*

assistant. To evaluate the quality of coding, both authors checked a random 20% sample (218 categories). The error rate in this sample was 0.92% so that about 13 call types are affected by coding errors, which extrapolates to 0.97% of all calls. Overall our coding results in 10.3% complaint calls and 66.9% other service requests in 2010 (see Table B1 for example categories). We exclude the remaining 22.8% calls as ambiguous. We aggregate the number of complaints and other service requests to the census block level. On average, there are 3.81 complaint calls and 30.7 other calls in a census block in 2010.