**The Action is Everywhere, but Greater at More Localized Spatial Scales:**

**Comparing Concentrations of Crime across Addresses, Streets, and Neighborhoods**

**Abstract:**

*Objectives*:Urban criminologists have long debated which geographic scale is most relevant to understanding the clustering of crime and disorder across a city. This study advances this conversation by comparing concentrations of crime at addresses, streets, and neighborhoods. It uses modified Gini coefficients to disentangle the three levels while also accounting for artifacts of arithmetic and urban form.

*Methods*:The study uses geocoded requests for emergency and non-emergency services received by the City of Boston’s 911 and 311 systems in 2011 to calculate six indices of violent crime, physical disorder, and social disorder for addresses (*N* = 98,355) nested in street segments (*N*  = 13,048) nested in census tracts (*N* = 178). These units were the basis for Gini coefficients, including “nested” Gini coefficients that assessed the average concentration at one level contained with a higher geographic unit (e.g., the streets of a single tract).

*Results*:Controlling for factors of arithmetic and urban form, the nested Gini coefficients found that concentrations were greatest at addresses, then at streets, then at tracts. Compared to whole-city calculations, they showed equal or greater levels of concentration of crime and disorder for addresses, but lower concentrations for streets. Controlling for the number of locations on a street or in a tract also markedly diminished concentrations.

*Conclusions*: All three geographic scales were relevant to concentrations of crime and disorder across the city, but more localized scales exhibited greater concentration. Theoretical implications for integrating multiple geographic scales in the study of concentrations of crime are discussed.

**Keywords:** Law of concentration of crime; physical disorder; social disorder; violent crime; computational social science; problem properties; hotspots

**INTRODUCTION**

One of the basic motivations for urban criminology is the observation that crime and disorder are unevenly distributed across the urban landscape. Over the years, though, researchers have adopted multiple perspectives regarding which geographic scale of analysis is most appropriate for observing and understanding this variation. Classical thought emphasized “high-risk neighborhoods” ([e.g., Shaw and McKay 1942/1969](#_ENREF_51); [Park, Burgess, and McKenzie 1925/1984](#_ENREF_43); [also see Sampson 2012](#_ENREF_47)), but recent trends have redirected attention to more localized contexts, including “hotspot streets” (e.g., [Weisburd 2015](#_ENREF_58); [Weisburd, Groff, and Yang 2012](#_ENREF_59); [Braga, Papachristos, and Hureau 2010](#_ENREF_9); [Andresen and Malleson 2011](#_ENREF_1)) and “problem properties” (or “hotdots”; [Sherman, Gartin, and Buerger 1989](#_ENREF_52); [O'Brien and Winship 2017](#_ENREF_41); [Farrell and Pease 2001](#_ENREF_20); [Johnson, Bowers, and Hirschfield 1997](#_ENREF_30)). Although considerable work has provided evidence for the relevance of each of these geographic scales, only a few studies have analyzed them simultaneously in order to compare their relative levels of concentration. This is a particularly tricky task because these geographic scales are inherently interdependent—addresses sit on streets which lie within neighborhoods—creating the need for analytic approaches that can disentangle concentrations at one level from the others.

The current study uses a database of requests for government services (i.e., 911 and 311 calls) from Boston, MA, to examine the relative concentration of six types of crime and disorder at addresses, street segments, and census tracts. This is done through the calculation and analysis of Gini coefficients, which quantify inequality in a distribution. More than just compare raw Gini coefficients at each level, the study extends the technique to address three challenges to the interpretation of concentrations of crime and disorder: 1) the arithmetic consequences of the rarity of crime, which can inflate Gini estimates; 2) aspects of urban form that can influence the distribution of crime and disorder, including land use and the mere density of locations where such events might occur; 3) leveraging the concept of nesting to create Gini coefficients that quantify concentration at one geographic scale independent of the others. Altogether, these techniques permit a comprehensive assessment of concentration at all three levels, controlling for multiple arithmetic and compositional artifacts that have occluded previous work. Before presentation of data and analyses, the proceeding sections summarize in greater depth how the history of the study of crime concentrations and the statistical and conceptual challenges facing their examination shape the current study.

*Concentrations of Crime: A Methodological Challenge*

Scholars have sought to understand the uneven distribution of outcomes across a city’s neighborhoods for at least 150 years (e.g., [Booth 1903](#_ENREF_6); [Mayhew 1862](#_ENREF_36)), making it one of the oldest themes in urban science. In the early 20th century, the Chicago School of Sociology took particular aim at this subject, probing inequalities in crime, health, and education across communities ([Shaw and McKay 1942/1969](#_ENREF_51); [Park and Burgess 1925](#_ENREF_42)). This work has since provided the conceptual basis for decades of research on the social, demographic, and physical features of neighborhoods that can influence local levels of crime ([Sampson, Raudenbush, and Earls 1997](#_ENREF_49); [Raudenbush and Sampson 1999](#_ENREF_46); [Cohen et al. 2000](#_ENREF_14); [Leventhal and Brooks-Gunn 2000](#_ENREF_35); [Browning, Soller, and Jackson 2015](#_ENREF_12); [Kawachi and Berkman 2003](#_ENREF_31); [Gibson et al. 2010](#_ENREF_22)). A more recent line of work, however, has highlighted the extent to which *microplaces*, or streets and addresses, contribute to the distribution of outcomes, most notably crime and disorder, across the city. This “criminology of place” has debunked the assumption that neighborhoods are homogenous regions, demonstrating that many streets in high-crime neighborhoods actually experience little crime, and that, conversely, there are high-crime streets in low-crime neighborhoods.

Criminology of place began with two studies in the late 1980s in two different cities, each demonstrating that ~3% of addresses accounted for 50% of crime events ([Sherman, Gartin, and Buerger 1989](#_ENREF_52); [Pierce, Spaar, and Briggs 1988](#_ENREF_44)). This discovery was revelatory at a time when neighborhoods were the primary focus for urban criminology. In the years that have followed, research in this area has largely converged upon “hotspot” street segments as the geographic scale of greatest interest, finding that, across cities, 4-6% of streets consistently generate 50% of crime events ([Braga, Papachristos, and Hureau 2010](#_ENREF_9); [Andresen and Malleson 2011](#_ENREF_1); [Weisburd 2015](#_ENREF_58)). Nonetheless, there has also been evidence that concentrations exist at an even more granular level, with a corresponding literature on repeat victimization identifying “hotdot” addresses that experience multiple crimes, most notably burglaries (e.g., [Farrell and Pease 2001](#_ENREF_20); [Johnson et al. 2007](#_ENREF_29); [Trickett et al. 1992](#_ENREF_56)). Similarly, an additional recent study replicated the earliest findings of criminology of place by showing that <2% of addresses accounted for 50% of events across six categories of crime and disorder in a single city ([O'Brien and Winship 2017](#_ENREF_41)). The consistency of these findings across locales and types of crime has led Weisburd (2015) to propose the *law of concentration of crime*: that for a given microgeographic unit there is a narrow bandwidth of percentages for a defined cumulative proportion of crime events.

Criminology of place has successfully demonstrated that “microplaces matter,” offering a counterpoint to the neighborhood-centric perspective that characterized the field. That said, affirming the importance of street segments and addresses is only a first step; a comprehensive understanding of concentrations of crime requires the simultaneous consideration of all three geographic levels and their relative contributions to the distribution of crime across the city. Some early work examined streets and neighborhoods together mainly to reach the conclusion that streets offer additional information that is not available through an exclusive focus on neighborhoods ([Andresen and Malleson 2011](#_ENREF_1); [Groff, Weisburd, and Yang 2010](#_ENREF_23)), but this is not the same as evaluating how much information each level contributes. We might then consider three main methodologies to target this question more directly. First, the most popular approach to concentrations of crime has been the use of proportions, for example, determining what percentage of units account for 50% of crime events. While evocative, it has not been used for comparisons as it does not support formal statistical testing. Second, multilevel models nest units from two or more geographic scales within each other (e.g., addresses on streets in neighborhoods), and can partition variance across these levels, thereby describing the relative contribution of each to the total variation in crime and disorder across the city. This technique has been used by a handful of studies (e.g., [Steenbeek and Weisburd 2016](#_ENREF_55); [Schnell, Braga, and Piza 2017](#_ENREF_50); [Tseloni 2006](#_ENREF_57)), though only one has examined addresses, streets, and neighborhoods simultaneously ([O'Brien and Winship 2017](#_ENREF_41)). Third, the Gini coefficient offers a standardized measure of inequality , and Bernasco and Steenbeek ([2017](#_ENREF_4)) have suggested that it might be used for direct comparisons across cities, especially with the calculation of standard errors via bootstrapping. The same approach might be repurposed to compare geographic scales in a single city.

Multilevel models and Gini coefficients offer two potential tools for comparing concentrations of crime across geographic scales, but neither is fully equipped in its traditional form to handles some of the challenges that this question poses. We can categorize them in three groups: 1) the difficulty of disentangling and then comparing concentrations at multiple geographic scales; 2) statistical artifacts that arise from the rare nature of crime; 3) the possibility that concentrations of crime might result from the varied organization of the city. By examining each further, it might be possible to develop a modified methodology that can effectively answers the question at hand.

1. Disentangling Nested Geographic Scales

Comparing levels of concentration across geographic levels within a single city is problematic. Essentially, such an analysis distributes the same set of events over geographic units that are nested within each other, meaning the level of concentration at one level is dependent on others. This makes it difficult to disentangle which levels are contributing most strongly. For example, take a city where crime rates are unevenly distributed across neighborhoods. Suppose then that those crimes are distributed perfectly evenly across the streets of each neighborhood. In this case, it would be inaccurate to attribute any of the distribution of crime to streets. Nonetheless, if streets are analyzed directly, they will appear to exhibit just as much concentration as neighborhoods because they are merely a more granular depiction of the same inequalities. Put in terms of basic arithmetic, shifting to a more localized geographic scale means distributing the same number of events across a far greater number of units. Thus, concentrations will inevitably look greater. The more appropriate question, then, is how much of the concentration of crime observed across streets is greater than what would be expected given known disparities between neighborhoods?

Disentangling each geographic level’s contribution to the distribution of crime requires analytic techniques that attend to nesting, which is the specialty of multilevel models ([Raudenbush and Bryk 2002](#_ENREF_45)). Multilevel models decompose variance across two or more levels by only analyzing units at one level in relation to other units in the same “nest,” or containing unit of the next highest geographic level. For example, it compares each street to other streets in the same tract, and then compares tracts to each other. This permits an estimation of the proportion of overall variation in crime for which each level is responsible. An important caveat, however, is that these comparisons will be strictly relative because the total percentage of variance must add up to 100%. Consequently, the assessment of concentration at each level is contingent on the amount of variance at the others; if one level has particularly high levels of concentration, it will make concentrations at other levels look quite small even if they are noteworthy in an absolute sense. The relative nature of this metric also makes comparisons of concentrations across cities impossible. In contrast, though the Gini coefficient does calculate absolute levels of concentration that are inherently comparable across scales and cities, it does not take into account nesting. In this sense, neither is perfectly suited to this problem.

Given the complementary strengths and weaknesses of multilevel models and the Gini coefficient, a combined approach would be most effective. Specifically, one might calculate Gini coefficients in a manner consistent with the analytic nesting of multilevel models. Instead of assessing concentration across all units in a city, one would do so for the addresses of a single street, or the streets of a single tract. The distribution of these separate Gini coefficients would then be a robust estimate of the extent to which concentrations at each of those levels are independent of variation existing at higher geographic scales.

1. Statistical artifacts

The rarity of crime and disorder creates an arithmetic difficulty for analyzing their concentration that hinders the interpretation of the most suitable methodologies. This is especially true for addresses and street segments, many of which do not generate any crime and disorder. This is problematic for multilevel models because the large number of zeroes at lower levels of aggregation exaggerates the overall variation. Indeed, O’Brien and Winship (2017) found that addresses accounted for 95-99% of the variance in six categories of crime and disorder, reflecting the fact that the vast majority of addresses in any street or tract had zero events, whereas others had dozens. Similarly, if there are more units then events, the Gini coefficient will generate an inflated estimate of inequality. For example, if there are three units and only one event, then it must have occurred at only one unit. According to the Gini, this is a maximally unequal distribution, with one unit accounting for 100% of events, but it is also technically the most equitable distribution possible. Bernasco & Steenbeek (2017) have forwarded a modified Gini coefficient that solves this issue by comparing a distribution to the minimum amount of inequality possible with the given number of units and events.

Analyses of crime concentrations to date have failed to address a second arithmetic consideration. Crime and disorder are events, and therefore would be expected to have a Poisson distribution, which is by definition uneven. Thus, research in this area has implicitly compared levels of concentrations to an even distribution, rather than the *expected* distribution given a particular number of events distributed across a specified number of units. Again, the Gini coefficient would lend itself to simple simulations that could estimate the expected level of unequal distribution.

1. Artifacts of Urban Form

One of the founding premises of criminology of place, rooted in routine activities theory ([Cohen and Felson 1979](#_ENREF_15)), is that aspects of urban form, like land usage (e.g., [Eck 1994](#_ENREF_18); [Bichler, Schmerler, and Enriquez 2013](#_ENREF_5))\_\_ or proximity to transportation hubs ([e.g., Caplan, Kennedy, and Miller 2011](#_ENREF_13))\_\_, can create localized concentrations of crime. For example, detached housing attracts more burglaries ([Bowers and Johnson 2005](#_ENREF_7)) and street segments with businesses tend to attract more robberies ([Smith, Frazee, and Davison 2000](#_ENREF_53)). It is possible, in turn, that global estimates of concentration of crime at a particular geographic scale are driven in part by the clustering of such characteristics. This has been visible in two studies on street-level patterns in crime that have found that hotspots tend to form linear clusters along thoroughfares ([Curman, Andresen, and Brantingham 2015](#_ENREF_16); [Groff, Weisburd, and Yang 2010](#_ENREF_23)). This would suggest that the potential for crime is concentrated at the neighborhood level, and then further concentrated within the neighborhood at places that share certain critical features, in this case a main street with lots of businesses. Thus, it is necessary to consider such factors in order to determine the extent to which they are responsible for clustering at each geographic scale.

Given the need to consider features of urban form as covariates, their incorporation into multilevel models would seem to make the most logical sense, but such studies to date have not explicitly tested the extent to which urban form accounts for concentrations of crime. For example, though O’Brien & Winship (2017) controlled for such features in their multilevel models, they did not quantify the extent to which this increased or decreased the relative variance presence at each geographic level. Other multilevel model studies \_\_\_\_? Even if such models were specified in this way, however, as described above it would still be difficult to compare levels of concentration across levels. Alternatively, such models could be used to calculate the number of crimes above expected for all locations in a city. These adjusted values could then be used as the basis for Gini coefficients. Though this adds an extra step, it would enable a more consistent interpretation of concentration at multiple geographic scales.

*Current Study*

The current study compares levels of concentration of crime across the City of Boston at three different geographic scales: addresses, street segments, and neighborhoods (approximated with census tracts). It utilizes an archive of records from the City’s 911 and 311 systems, which receive and compile requests for non-emergency (e.g., graffiti removal) and emergency (e.g., shooting) government services, respectively. Based on previous work with these records, the study will examine six categories of crime and disorder, defined as the combination of particular case types. These include physical disorder in private and public spaces, social disorder in private and public spaces, and violent crime with and without guns ([O'Brien and Sampson 2015](#_ENREF_38); [O'Brien and Winship 2017](#_ENREF_41)). The records will be analyzed in conjunction with a multilevel database that organizes the geography of the city into 17 levels. This Geographical Infrastructure includes basic descriptors of urban form at each of the three levels of interest while also providing a tool for nesting levels within each other (e.g., addresses on street segments within tracts), both of which are central to the analysis that follows ([O'Brien and Gomory 2017](#_ENREF_37)).

The study will use Gini coefficients as standardized measures of inequality in the distribution of crime and disorder across units. In order to account for the challenges raised above, the Gini analyses will be implemented with three modifications. First, whenever units outnumber events of crime or disorder, the study will use the modified Gini (*G’*) proposed by Bernasco and Steenbeek (2017). Second, in order to disentangle levels of concentration at each of the geographic scales, the study will examine the distribution of events across the units at one level contained in a single, higher-level unit. For example, a Gini coefficient will be calculated for the distribution of gun-related calls across the addresses of a given street. The analysis that follows will then assess the mean Gini across all streets, thereby estimating the level of concentration of gun-related events at addresses while accounting for the number of such events occurring on a given street. Third, the study will use residuals from multilevel models to re-estimate Gini coefficients based on the number of crime and disorder events above expected, thereby controlling for aspects of urban form. Altogether, these techniques should permit a robust comparison of concentration across levels.

**METHODS AND DATA**

*Data Sources and Measures*

The study utilizes the archive of requests for service received by the City of Boston’s 311 system and dispatches made by the 911 system in 2011. For the 311 system, this includes requests received by hotline as well as associated web platforms (e.g., smart phone application). During 2011 the City received 153,731 unique requests through the 311 system[[1]](#footnote-1) and made 560,393 911 dispatches. Of these, 141,062 311 requests and 525,183 911 dispatches referenced an address or intersection that could be uniquely identified in the list of known locations maintained by the City of Boston (see below), reflecting the equivalent of geocoding rates of 92% and 94%, respectively.[[2]](#footnote-2) Data were further limited to those events attributed to an address (i.e., excluding intersections; 114,029 311 reports and 491,488 911 dispatches). Importantly, these locations are the location where services were required, not necessarily the location from which the request was made. Each system utilizes a standardized list of case types to categorize all requests at the time of receipt, capturing the nature of the issue and the services required. All records also contain the date and time the request was received.

Previous work with Boston’s 311 and 911 archives used confirmatory factor analysis to develop groupings of case types that act as indices of disorder and crime. 311 reports provided two indices of physical disorder (O’Brien et al. 2015): *private neglect*, comprised of cases referencing housing issues (e.g., rodent infestation), uncivil use of private space (e.g., illegal rooming house, illegal parking on yard), and problems with big buildings (i.e., apartments, condos); and *public denigration*, comprised of cases reflecting graffiti and the improper disposal of trash. 911 dispatches provided two indices of social disorder and two indices of violent crime ([O'Brien and Sampson 2015](#_ENREF_39)). The indices of social disorder were: *public social disorder*, such as panhandlers, drunks, and loud disturbances; and *private conflict* arising from personal relationships (e.g., domestic violence). The indices of violent crime were: *public violence* that did not involve a gun (e.g., fight); and *prevalence of guns*, as indicated by shootings or other incidents involving guns. Table 1 reports constituent case types for each index and their frequencies for 2011.

*Units of Analysis*

The City of Boston’s Street and Address Management system and Tax Assessor track all properties (i.e., the smallest ownable unit) and land parcels (i.e., geographically-bounded lots that contain one or more properties). Together these form the basis of the Boston Area Research Initiative’s Geographical Infrastructure for Boston ([GI; O'Brien and Gomory 2017](#_ENREF_37)), which then maps them both to U.S. Census TIGER line street segments (i.e., the undivided length of street between two intersections or an intersection and a dead end) and nests them within census blocks, block groups, and tracts, as well as other local administrative geographies. Because 311 and 911 requests do not reliably specify the individual property of interest within a land parcel (e.g., condominiums in a building), here we use land parcels as the fundamental unit of analysis and an approximation of the colloquial “address.” The City maintains its own list of land parcels, but the GI condenses this list slightly by combining distinct land parcels with the same postal address that are sufficiently close to each other to be impossible to differentiate. For our purposes here, this results in a final, three-level database of 98,355 land parcels (from hereon referred to as addresses) situated on 13,048 street segments within 178 census tracts.[[3]](#footnote-3) This nested structure forms the basis for analyses of the distribution of crime and disorder of units within the next highest level of organization (e.g., the addresses on a street).[[4]](#footnote-4) The GI also provides information on urban form that may be relevant to the expected level of crime and disorder at a place, including: land usage for each parcel (e.g., Residential, Commercial) and an estimate of the number of units (either as a sum of parcels or the number of units identified by the tax assessor [e.g., Two-Family Residential contains 2 units]); the street’s length, identification as a Main street (provided by MassGIS), and nature of land usage (a seven-group typology based on a cluster analysis of the representation of each land use); the tract’s population, number of households, and type (e.g., Residential, Downtown, Park). Table 2 reports descriptive statistics for each of these characteristics.

*Analysis*

The main analysis centers on the calculation of Gini coefficients, following the classical equation:

where one has a population of *n* units each with a value *y* (e.g., addresses with a quantity of gun-related crime reports). When there are fewer events than units, the analysis uses the modified Gini coefficient proposed by Bernasco and Steenbeek (2017):

These calculations are conducted in R using the reldist package’s gini command ([Handcock 2016](#_ENREF_24)) in conjunction with custom functions. For what will be referred to as global analyses of distribution, the Gini coefficient (i.e., *G* or *G*’, as appropriate) is calculated for all units across the city. For what will be referred to as nested analyses, Gini coefficients are calculated for each “nest” and the central tendency and distribution of this distribution of Gini coefficients is then used to evaluate concentrations at the lower geographic scale. For example, to examine concentrations of crime and disorder at addresses, the nested analyses calculated the Gini coefficient for all 13,047 streets with one or more addresses.

Simulations are run in order to evaluate whether Gini coefficients indicate levels of concentration above and beyond what would be expected given the number of events and units. For each calculated Gini coefficient, 10,000 Poisson distributions with the same number of events and units were generated, and the average of these 10,000 simulated Gini coefficient was used as the point of comparison. For global analyses of all units at a geographical level, this comprised a single simulated expected Gini coefficient. For nested analyses, this comprised a simulated expected Gini coefficient for all higher-level units. For example, an expected Gini coefficient was simulated for all 13,047 streets, based on the number of addresses and events associated with each. These were then analyzed in aggregate, paralleling the analysis of the actual Gini coefficients.

**RESULTS**

*Descriptive Statistics and Global Analyses of Concentration*

All six forms of disorder and crime were rare events relative to the number of addresses and streets (see Table 3). Even the most common category, public violence, featured one event per seven addresses (*M* = 0.15) and was the only one with more events than streets (*M* = 1.27). Others were particularly rare, with the prevalence of guns featuring one event per fifty addresses (*M* = .02). Nonetheless, ranges were quite high (*maxima* = 25 – 81 events at an address) and the standard deviations of counts per address and street were universally greater than the corresponding means. This latter point reflects a strong skew, violating the Poisson distribution and suggesting that the events are not randomly distributed across locations. The story was less extreme for tracts, with the number of events per tract ranging from 9.59 to 81.87 across categories. Corresponding standard deviations were nearer to these values, more in keeping with a true Poisson distribution.

When estimating global Gini coefficients, it was necessary to use the modified *G*’ for all six categories for addresses, and for streets for all categories apart from public violence.[[5]](#footnote-5) Gini coefficients indicated that, when considering the entire city as a whole, concentrations for all types of crime and disorder were highest at the street level (*G*’s = .56 - .85), then at the address level (*G*’s = .43 - .76), and lowest at the tract level (*G*s = .41 - .51). For point of comparison, the simulated Ginis (see Methods) indicated that the expected level of concentration was far higher for streets (E(*G*’)s =.12 - .50) than for addresses (E(*G*’)s = .02 - .13) or tracts (E(*G*’)s = .06 - .18). From this perspective, one might argue that addresses have the most notable concentrations relative to statistical expectations.[[6]](#footnote-6) Nonetheless, the interpretation is ambiguous, not to mention that concentrations at one level are partially attributable to those below it when analyzing the data in this way.

*Nested Analyses of Concentration*

In order to disentangle concentrations of crime and disorder across levels, we can calculate Gini coefficients that nest the units of one level in the containing unit of the next-highest geographic level. For example, given the number of gun-related events in a tract, to what extent were they concentrated at certain streets in the tract more than others? This permits an examination of the level of concentration at addresses or streets independent of an existing concentration at a higher level of geography. This technique will generate a Gini coefficient for every street (i.e., the unequal distribution of crimes across the addresses of that street) and tract (i.e., the unequal distribution of crimes across the streets of that tract). We can then compare the typical level of concentration across levels. To avoid outliers, we only calculate Gini coefficients for streets and tracts that have 5 or more events of a given type of crime or disorder and 5 or more lower-level units (i.e., addresses or streets, respectively; except in the case of prevalence of guns, whose rarity require a threshold of 4 events and units to permit sufficient variation to be analyzable).

The analysis of nested Gini coefficients occurs in two steps. First, Gini coefficients based on raw counts of events are calculated. Second, they are re-calculated using estimates of the number of events above expected for each unit based on aspects of urban form. For each stage, it is necessary to calculate a “typical” level of concentration for addresses in streets and streets in tracts. Because Gini coefficients inherently vary with the number of units and events distributed across them, in order to fairly compare across levels we will run regressions using those two variables to predict Gini coefficients. All values reported from hereon will reflect the estimate for 5 events and 5 lower-level units.[[7]](#footnote-7) These regressions are reported in the Appendix.

Distribution of Raw Counts

The nested Gini coefficients differed from the global Gini coefficients in a few ways. Most notably, whereas crime concentrated across the addresses of a given street about equally if not more highly than across all addresses in the city (*G’*s = .61 - .73; equal or higher than the global analysis for 5 of 6 categories), streets tended to show *less* concentration when nested in tracts, with Gini coefficients dropping by as much as a third (*G’*s = .41 - .70; lower than the global analysis for all categories). This suggests that the high concentration of crime and disorder at street segments across the city is partially attributable to variations across census tracts. In contrast, variations at higher geographic scales were not responsible for the concentrations seen at addresses. Further, events were universally more concentrated across the addresses of a street than the streets of a tract, though these two values were more comparable for some categories (e.g., private neglect, public violence) than others (e.g., public social disorder, prevalence of guns). Again, all Gini coefficients were far higher than those expected for a Poisson distribution of comparable number of events and units (addresses: E(*G’*)s = .31 - .37; streets: E(*G’*)s = .17 - .36).[[8]](#footnote-8)

Because tracts were not nested, we compare the global assessments to the other levels. Notably, the lowered Gini coefficients for streets when nested were comparable to tract-level concentrations for a number of measures, including public denigration and public social disorder; most notably, prevalence of guns was much more concentrated for tracts than streets (.58 vs. .41).

Distribution of Events above Expected

The initial analysis of nested Gini coefficients separated concentrations at one level from the variations at higher levels of geographic organization, but did not attend to inherent differences in the distribution of events based on urban form. It is possible that some portion of these concentrations are a consequence of similar types of properties being clustered in space. Here we use multilevel models to calculate the expected number of events of a given type of disorder or crime for each address in the city relative to addresses on the same street, based on the number of parcels it contains and its land use (see Appendix for full details). The result is a *count of events above expected*.[[9]](#footnote-9) We can then do the same for street- and tract-level characteristics that are predictive of the number of events at the average address therein. It is only relevant to analyze these values at the geographic level of the controls and above, however, as they will alter the estimated count of events for all addresses therein (and, in the case of tract-level characteristics, all streets). We then take account of the number of addresses on each street and streets in each tract, acknowledging the possibility that these higher-order geographies might see concentrations based in part on the uneven distribution of locations where crime and disorder might occur.

Controlling for address characteristics had little if any impact on the Gini coefficients at all three levels (addresses: Δ*G*’s = .00 - .01; streets: Δ*G*’s = .00 - .01; tracts: all Δ*G*’s = .00). The same was true for controlling for street characteristics (streets and tracts: all Δ*G*’s = .00) and tract characteristics (tracts: Δ*G*’s = .00 - .01). Controlling for the number of addresses on a street and number of streets in a tract, however, had more substantial impacts on concentrations. Accounting for the number of addresses on a street lowered the estimated concentration of crime and disorder across the streets of a tract markedly, with Gini coefficients dropping by as much as 20% (Δ*G*’s = .01 - .12). Even more pronounced, inequality across tracts was cut nearly in half once the number of streets in a tract was taken into account (Δ*G*’s = .11 - .23). In sum, these adjustments for the physical composition and organization of the city left address-level concentrations largely intact (*G*’s ≈ .6 - .7) while diminishing concentrations at the street (*G*’s ≈ .4 - .5, with two outliers ≈ .6 - .7) and tract levels (*G*’s ≈ .2 - .3 with one value ≈ .4).

**DISCUSSION**

The results bring new clarity to an empirical debate that has become prominent in recent years: which geographic level is the most important to the distribution of crime and disorder across a city, or, as some have quipped, “where is the action?” The analysis here made this question tractable by using Gini coefficients in conjunction with three techniques. First, it used a modified Gini coefficient that could account for situations in which the units outnumber the events that are distributed across them ([Bernasco and Steenbeek 2017](#_ENREF_4)). Second, it used the logic of nesting to disentangle concentrations from one geographic level (e.g., addresses) from existing concentrations at higher levels (e.g., streets). Third, it controlled for aspects of urban form whose own clustering might drive concentrations of crime, like land use and the density of locations where crime and disorder might occur. After accounting for these conditions and factors, concentrations were consistently greatest across addresses, then streets, and least so for tracts. The action, then, is “everywhere,” but becomes increasingly prominent as one zooms in to more and more localized spatial scales.

Strictly speaking, the finding that concentrations are greater at lower spatial scales is not all that different from previous studies. The few comparisons of streets and neighborhoods ([Schnell, Braga, and Piza 2017](#_ENREF_50); [Steenbeek and Weisburd 2016](#_ENREF_55)), addresses and neighborhoods ([Tseloni 2006](#_ENREF_57)), and the one comparison of all three levels have observed the same basic relationship ([O'Brien and Winship 2017](#_ENREF_41)). That said, the more comprehensive methodological approach taken here tempered the dramatic differences in concentration observed through multilevel models, which are vulnerable to the abundance of zeroes at lower levels of aggregation. As importantly, we saw how the various considerations of the analysis impacted estimates of concentration. Three such results are worth noting. First, Gini estimates at the street level dropped by ~20% when streets were nested within tracts, but the same effect was not seen for addresses. In some cases the nested analysis increasedthe Gini estimates for addresses. This would indicate that a substantial proportion of the concentration of crime at streets is attributable to variations in crime between tracts. Put another way, the distribution of crime across the streets of a tract was more equitable than across all the streets of the city. In contrast, concentrations of crime and disorder at addresses were especially prominent at the local level, possibly because there are many problem properties across the city, but the typical hotspot street segment is dominated by a single such property. Second, controlling for the number of locations in a geography (e.g., addresses on a street) markedly lowered Gini coefficients, especially for tracts, implying that some places have more crime and disorder simply by virtue of having more places where such events can occur. This should not be an entirely surprising finding, but highlights the fact that this consideration has so rarely been addressed in the criminology of place literature.

The third finding of interest was in fact the lack of an effect. Controlling for land use at each of the three levels had negligible impact on all estimates of concentration of crime and disorder. Even though there is considerable evidence that such characteristics do influence the routine activities and therefore crime and disorder at a place ([Eck 1994](#_ENREF_18); [Bichler, Schmerler, and Enriquez 2013](#_ENREF_5); [Johnson 2008](#_ENREF_28); [Johnson et al. 2007](#_ENREF_29); [Bowers and Johnson 2005](#_ENREF_7); [Smith, Frazee, and Davison 2000](#_ENREF_53)), this would indicate that such effects do not drive overall patterns of concentration. Instead, there are patterns and processes associated with specific places across the city, independent of their land use, that underlie the emergence and persistence of problem properties, hotspot streets, and high-risk neighborhoods.

Before discussing the theoretical implications of these findings, it is important to acknowledge a few limitations of the work. First, the analysis is of a single city and will need to be joined by replications in other locales, especially of different sizes or in other countries. Because Gini coefficients are absolute measures, they facilitate the pursuit and implementation of such a research agenda. Second, while the advent of high-quality, digital administrative records has been a recent boon to criminology of place and to urban science more generally, they have their weaknesses as a resource for research ([Lazer et al. 2014](#_ENREF_33); [Lazer et al. 2009](#_ENREF_34); [O'Brien, Sampson, and Winship 2015](#_ENREF_40); [Boyd and Crawford 2012](#_ENREF_8)). Most importantly, they are subject to the biases of the data-generation mechanism, in this case the decision of constituents to report events. For example, [Klinger and Bridges (1997)](#_ENREF_32) found evidence of both erroneous reports (i.e., false positives) and unreported crimes (i.e. false negatives) in constituent calls for service, resulting in a moderate skew in cross-neighborhood crime estimates. More recently, [O'Brien, Sampson, and Winship (2015)](#_ENREF_40) identified differences in “custodianship” that led some neighborhoods to be more likely to report deterioration in the public domain less reliably than others. The skew was more limited for reports regarding the deterioration and misuse of private property. There is reason to believe, however, that there are fewer such concerns for more general analyses of concentration and persistence. Hibdon et al. ([2017](#_ENREF_26)) found that two service request systems in Seattle, WA, identified different hotspots for drug activity, but still described the same overall pattern of concentrations.

*Implications for Theory: Bottom-Up and Top-Down Distributions of Crime and Disorder*

Much of the discussion of concentrations of crime has centered on which geographical scale or scales matter, but they raise a deeper conceptual question about what concentrations at each of these levels indicate about the geographical organization of crime and of social dynamics more generally. For instance, we see the lowest level of concentrations at the tract level, but one might note that neighborhood-focused criminologists have rarely if ever used the term “concentration,” focusing more on “between-neighborhood variation.” This is more than just a semantical point. It exposes two contrasting theoretical models of how differences in crime across places might emerge. Some proponents of the law of concentration of crime talk about “normal” levels of concentration that are maintained across contexts and types of crime ([Weisburd, Groff, and Yang 2012](#_ENREF_59)). This presupposes a certain propensity for crime in a place or region, the manifestations of which are then distributed to the locations therein. These events then become highly concentrated in a small number of locations. We might call this the *top-down* model. Alternatively, neighborhood researchers treat each neighborhood as an independent entity with its own characteristic level of crime, and their aggregation determines the overall level and variation of crime in the city. We might call this the *bottom-up* model.

Though seemingly at odds, the top-down and bottom-up models of geographic variation in crime are not incompatible, notably because variations at different levels of geographic organization very well might be driven by different mechanisms. It would seem unlikely that crime rates are characteristic of an entire city and then distributed across neighborhoods. Though there is some evidence, particularly for burglary, of criminals transporting strategically across the city to attractive sites ([Bernasco, Johnson, and Ruiter 2015](#_ENREF_3)), but the vast majority of crime and disorder is generated by actors who live nearby. Thus, consistent with the long-standing neighborhood-centric literature, each neighborhood’s crime rate is largely a function of local demographics and social dynamics (e.g., [Sampson 2012](#_ENREF_47); [Sampson and Raudenbush 1999](#_ENREF_48); [Sampson, Raudenbush, and Earls 1997](#_ENREF_49); [Steenbeek and Hipp 2011](#_ENREF_54); [Harcourt and Ludwig 2006](#_ENREF_25); [Bellair and Browning 2010](#_ENREF_2)). Estimating the overall prevalence of crime and disorder in a neighborhood, however, does not tell us at which discrete locations such events are occurring. Those events must be distributed throughout the streets and at the addresses of the neighborhood. Whereas simplistic approaches to neighborhood effects might have assumed that all locations in a high-crime neighborhood have an equally elevated risk for crime events, work by criminologists of place have shown that crime is more apt to concentrate at a small number of streets and addresses.

The integrated perspective does rely on two main assumptions, though the results here and in previous work appear to bear them out. First, it assumes that neighborhoods are socially-meaningful units, a concept that was the foundation of early urban science but has been since called into question ([Hipp and Boessen 2013](#_ENREF_27)). One could alternatively argue, as some criminologists of place have done, that street segments are the basic unit of social geography, and that their aggregations determine the nature of both neighborhoods and the city they constitute. Though the analyses here cannot rule out this possibility, previous studies with multilevel models have found that neighborhoods do account for significant amounts of variation in crime even when considering addresses and streets ([Steenbeek and Weisburd 2016](#_ENREF_55); [O'Brien and Winship 2017](#_ENREF_41); [Schnell, Braga, and Piza 2017](#_ENREF_50); [Tseloni 2006](#_ENREF_57)). This is in keeping with a broader body of work on the effects that neighborhoods have on resident outcomes, over and above the impacts of individual-level characteristics (e.g., [Sampson 2012](#_ENREF_47); [Leventhal and Brooks-Gunn 2000](#_ENREF_35); [Diez Roux and Mair 2010](#_ENREF_17); [Browning et al. 2008](#_ENREF_10); [Browning and Cagney 2002](#_ENREF_11); [Emory et al. 2008](#_ENREF_19); [Franzini et al. 2005](#_ENREF_21)). Further, as highlighted above, the nested analyses substantially diminished the concentration of crime and disorder at streets. This provides evidence that concentrations at tracts are more than just the bottom-up aggregation of street-level concentrations. At the more localized level, this perspective assumes that addresses are not so granular to become socially uninteresting. To illustrate, suppose that a social system is coterminous with a street segment or census tract, then crime might occur at any of its addresses, independent of address characteristics. Based on the findings here and elsewhere ([O'Brien and Winship 2017](#_ENREF_41); [Tseloni 2006](#_ENREF_57)), it is apparent that addresses do matter and are more than just the street or tract of which they are a part.

We might then consider, in brief, a summary of crime variations that attends to all three levels: neighborhoods vary in their propensity for crime and disorder, but such events concentrate at hotspot streets within tracts—and, to an even greater extent, at problem properties on those streets. This premise offers guidance for research and practice moving forward, with a renewed emphasis on causality. Importantly, though concentrations of crime can be informative, the locus of crime and the locus of causality need not be the same thing. For example, even if crime is more strongly concentrated at streets and addresses, the current perspective would suggest that neighborhoods still play a meaningful hand in determining the levels of crime that a hotspot street or problem property can attain. There might also be arguments that the social dynamics of a neighborhood or street are responsible for creating the concentrations therein, delimiting where crime can and cannot occur ([Weisburd, Groff, and Yang 2012](#_ENREF_59)).

Studies that pursue questions of causality in addition to concentration would better reveal not only the geographic organization of crime, but also the social dynamics and physical contexts that shape it. This would hold both theoretical and practical value that goes beyond the current study. Without a thorough understanding of causal mechanisms, the results here can and should not be used to justify particular strategies of crime prevention and law enforcement. In particular, addresses might be the geographic scale with the highest level of concentration of crime, but it is still feasible that interventions that target problem properties will merely displace crime to other addresses on a street or in a neighborhood. With this in mind, the current study helps to answer a classical question on the distribution of crime across a city, but its greater value is probably in highlighting the need to answer these sorts of questions.

**REFERENCES**

Andresen, Martin A., and Nicolas Malleson. 2011. Testing the stability of crime patterns: Implications for theory and policy. *Journal of Research in Crime & Delinquency* 48 (1):58-82.

Bellair, P. E., and C. R. Browning. 2010. Contemporary Disorganization Research: An Assessment and Further Test of the Systemic Model of Neighborhood Crime. *Journal of Research in Crime and Delinquency* 47 (4):496-521.

Bernasco, Wim, Shane D. Johnson, and Stijn Ruiter. 2015. Learning where to offend: Effects of past on future burglary locations. *Applied Geography* 60:120-129.

Bernasco, Wim, and Wouter Steenbeek. 2017. More places than crimes: implications for evaluating the law of crime concentration at place. *Journal of Quantitative Criminology* 33:451-467.

Bichler, Gisela, Karin Schmerler, and Janet Enriquez. 2013. Curbing nuisance motels: An evaluation of police as place regulators. *Policing: An Intenational Journal of Police Strategies & Management* 36 (2):437-462.

Booth, Charles. 1903. *Life and Labour of the People in London*. London: Macmillan & co.

Bowers, Kate J., and Shane D. Johnson. 2005. Domestic burglary repeats and space-time clusters. *European Journal of Criminology* 2 (1):67-92.

Boyd, Danah, and Kate Crawford. 2012. Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society* 15 (5):662-679.

Braga, Anthony A., Andrew V. Papachristos, and David M. Hureau. 2010. The Concentration and Stability of Gun Violence at Micro Places in Boston, 1980-2008. *Journal of Quantitative Criminology* 26:33-53.

Browning, C. R., L. A. Burrington, T. Leventhal, and J. Brooks-Gunn. 2008. Neighborhood structural inequality, collective efficacy, and sexual risk behavior among urban youth. *Journal of Health and Social Behavior* 49 (3):269-285.

Browning, C. R., and K. A. Cagney. 2002. Neighborhood structural disadvantage, collective efficacy, and self-rated physical health in an urban setting. *Journal of Health and Social Behavior* 43 (4):383-399.

Browning, Christopher R., Brian Soller, and Aubrey L. Jackson. 2015. Neighborhoods and adolescent health-risk behavior: An ecological network approach. *Social science & medicine* 125:163-172.

Caplan, Joel M., Leslie M. Kennedy, and Joel Miller. 2011. Risk terrain modeling: brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly* 28 (2):360-381.

Cohen, Deborah, Suzanne Spear, Richard Scribner, Patty Kissinger, Karen Mason, and John Widgen. 2000. "Broken windows" and the risk of gonorrhea. *American Journal of Public Health* 90 (2):230-236.

Cohen, Lawrence E., and Marcus Felson. 1979. Social change and crime rate trends: A routine activity approach. *American Sociological Review* 44 (4):588-608.

Curman, Andrea S.N., Martin A. Andresen, and Paul J. Brantingham. 2015. Crime and place: A longitudinal examination of street segment patterns in Vancouver, BC. *Journal of Quantitative Criminology* 31:127-147.

Diez Roux, Ana V., and Christina Mair. 2010. Neighborhoods and health. *Annals of the New York Academy of Sciences* 1186:125-145.

Eck, John E. 1994. *Drug markets and drug places: A case-control study of the spatial structure of illicit drug dealing*. Ann Arbor, MI: University Microfilms International.

Emory, R., M. Caughy, I. R. Harris, and L. Franzini. 2008. Neighborhood social processes and academic achievement in elementary school. *Journal of Community Psychology* 36 (7):885-898.

Farrell, Graham, and Ken Pease. 2001. *Repeat Victimization*. Monsey, NY: Criminal Justice Press.

Franzini, L., M. Caughy, W. Spears, and M. E. F. Esquer. 2005. Neighborhood economic conditions, social processes, and selfrated health in low-income neighborhoods in Texas: A multilevel latent variables model. *Social science & medicine* 61 (6):1135-1150.

Gibson, C. L., C. J. Sullivan, S. Jones, and A. R. Piquero. 2010. "Does It Take a Village?" Assessing Neighborhood Influences on Children's Self-Control. *Journal of Research in Crime and Delinquency* 47 (1):31-62.

Groff, Elizabeth, David Weisburd, and Sue-Ming Yang. 2010. Is it important to examine crime trends at a local "micro" level: A longitudinal analysis of street to steet variability in crime trajectories. *Journal of Quantitative Criminology* 26:7-32.

reldist: Relative Distribution Methods 1.6-6, CRAN.

Harcourt, B. E., and J. Ludwig. 2006. Broken Windows: New Evidence from New York City and a Five-City Social Experiment. *University of Chicago Law Review* 73 (1):271-320.

Hibdon, Julie, Cody Telep, and Elizabeth Groff. 2017. The concentration and stability of drug activity in Seattle, Washington using oplice and emergency medical services data. *Journal of Quantitative Criminology* 33:497-517.

Hipp, John R., and Adam Boessen. 2013. Egohoods as waves washing across the city: A new measure of "neighborhoods". *Criminology* 51 (2):287-327.

Johnson, Shane D. 2008. Repeat victimisation: A tale of two theories. *Journal of Experimental Criminology* 23:201-219.

Johnson, Shane D., Wim Bernasco, Kate J. Bowers, Henk Elffers, Jerry Ratcliffe, George Rengert, and Michael Townsley. 2007. Space-time patterns of risk: A cross national assessment of residential burglary victimization. *Journal of Quantitative Criminology* 23:201-219.

Johnson, Shane D., Kate J. Bowers, and Alex F.G. Hirschfield. 1997. New insights into the spatial and temporal distribution of repeat victimization. *British Journal of Criminology* 37:224-241.

Kawachi, Ichiro, and Lisa F. Berkman, eds. 2003. *Neighborhoods and health*. Oxford, UK: Oxford University Press.

Klinger, David A., and George S. Bridges. 1997. Measurement error in calls-for-service as an indicator of crime. *Criminology* 35 (4):705-726.

Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. 2014. The parable of Google Flu: Traps in big data analysis. *Science* 343:1203-1205.

Lazer, David, Alex Pentland, Lada Adamic, Siana Aral, Albert-Laszlo Barabasi, Devon Brewer, Nicholas Christakis, Noshir Contractor, James Fowler, Myron Gutmann, Tony Jebara, Gary King, Michael Macy, Deb Roy, and Marshall van Alstyne. 2009. Computational social science. *Nature* 323:721-723.

Leventhal, Tama, and Jeanne Brooks-Gunn. 2000. The neighborhoods they live in: The effect of neighborhood residence on child and adolescent outcomes. *Psychological Bulletin* 126 (2):309-337.

Mayhew, Henry. 1862. *London Labor and the London Poor*. London: Griffin, Bohn.

O'Brien, Dan, and Henry Gomory. 2017. Geographical Infrastructure for the City of Boston (v. 2017), edited by B. A. R. Initiative. Harvard Dataverse.

O'Brien, Daniel, and Robert J. Sampson. 2015. Public and Private Spheres of Neighborhood Disorder: Assessing Pathways to Violence Using Large-Scale Digital Records. *Journal of Research in Crime and Delinquency* 52:486-510.

O'Brien, Daniel Tumminelli, and Robert J. Sampson. 2015. Public and private spheres of neighborhood disorder: Assessing pathways to violence using large-scale digital records. *Journal of Research in Crime and Delinquency* 52.

O'Brien, Daniel Tumminelli, Robert J. Sampson, and Christopher Winship. 2015. Ecometrics in the age of big data: Measuring and assessing "broken windows" using administrative records. *Sociological Methodology* 45:101-147.

O'Brien, Daniel Tumminelli, and Christopher Winship. 2017. The gains of greater granularity: The presence and persistence of problem properties in urban neighborhoods. *Journal of Quantitative Criminology* 33:649-674.

Park, Robert E., and Ernest W. Burgess. 1925. *The City*. Chicago, IL: University of Chicago Press.

Park, Robert E., Ernest W. Burgess, and Roderick D. McKenzie. 1925/1984. *The City: Suggestions for Investigation of Human Behavior in the Urban Environment*. Chicago: University of Chicago Press.

Pierce, Glenn L., Susan Spaar, and LeBaron R. Briggs. 1988. The character of police work: Stategic and tactical implications. Boston, MA: Center for Applied Social Research, Northeastern University.

Raudenbush, Stephen W., and Anthony Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis*. Thousand Oaks, CA: Sage Publications.

Raudenbush, Stephen W., and Robert J. Sampson. 1999. 'Ecometrics': Toward A Science of Assessing Ecological Settings, with Application to the Systematic Social Observation of Neighborhoods. *Sociological Methodology* 29:1-41.

Sampson, Robert J. 2012. *Great American City: Chicago and the Enduring Neighborhood Effect*. Chicago: University of Chicago Press.

Sampson, Robert J., and Stephen W. Raudenbush. 1999. Systematic Social Observation of Public Spaces: A New Look at Disorder in Urban Neighborhoods. *American Journal of Sociology* 105:603.

Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science* 277:918-924.

Schnell, Cory, Anthony A. Braga, and Eric L. Piza. 2017. The influence of community areas, neighborhood clusters, and street segments on the spatial variability of violent crime in Chicago. *Journal of Quantitative Criminology* 33:469-496.

Shaw, Clifford, and Henry McKay. 1942/1969. *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.

Sherman, Lawrence W., Patrick R. Gartin, and Michael E. Buerger. 1989. Hot spots of predatory crime: Routine activities and the ciminology of place. *Criminology* 27 (1):27-55.

Smith, William R., Sharon Glave Frazee, and Elizabeth L. Davison. 2000. Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology* 38 (2):489-524.

Steenbeek, Wouter, and John R. Hipp. 2011. A Longitudinal Test of Social Disorganization Theory: Feedback Effects among Cohesion, Social Control, and Disorder. *Criminology* 49:833-871.

Steenbeek, Wouter, and David Weisburd. 2016. Where the action is in crime? An examination of variability of crime across different spatial units in The Hague, 2001-2009. *Journal of Quantitative Criminology* 32 (3):449-469.

Trickett, Alan, Denise R. Osborn, Julie Seymour, and Ken Pease. 1992. What is different about high crime areas? *British Journal of Criminology* 32 (1):81-89.

Tseloni, Andromachi. 2006. Multilevel modelling of the number of property crimes: Household and area effects. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 169 (2):205-233.

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: Oxford University Press.

**Table 1.** Case types composing the indices of physical disorder (311 reports), social disorder, and violent crime (911 dispatches), and their frequencies at addresses in 2011.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Case Type** | **Count** |  | **Case Type** | **Count** |  | **Case Type** | **Count** |
| **Physical Disorder** | | | | | | | |
| *Private Neglect* | |  | Maintenance – Homeowner | 72 |  | Unsatisfactory Utilities – Electrical, Plumbing | 89 |
| Abandoned Building | 90 |  | Maintenance Complaint – Residential | 255 |  |  |  |
| Bed Bugs | 368 |  | Mice Infestation – Residential | 396 |  | *Public Denigration* | |
| Big Buildings Enforcement | 88 |  | Parking on Front/Back Yards (Illegal Parking) | 119 |  | Abandoned Bicycle | 52 |
| Big Buildings Online Request | 67 |  | Pest Infestation – Residential | 120 |  | Empty Litter Basket | 157 |
| Big Buildings Resident Complaint | 58 |  | Poor Conditions of Property | 913 |  | Graffiti Removal | 2451 |
| Breathe Easy | 234 |  | Poor Ventilation | 13 |  | Illegal Dumping | 692 |
| Chronic Dampness/Mold | 184 |  | Squalid Living Conditions | 42 |  | Improper Storage of Trash (Barrels) | 1574 |
| Heat - Excessive, Insufficient | 1006 |  | Trash on Vacant Lot | 113 |  | PWD Graffiti | 83 |
| Illegal Occupancy | 262 |  | Unsatisfactory Living Conditions | 4351 |  | Rodent Activity | 1192 |
| Illegal Rooming House | 177 |  |  |  |  |  |  |
| Lead | 55 |  |  |  |  |  |  |
| **Social Disorder** | | | | | | | |
| *Public Social Disorder* | |  | Vandalism in Progress | 634 |  | Landlord/Tenant Trouble | 666 |
| Intoxication: Individual | 932 |  |  |  |  | Vandalism Report | 3408 |
| Drunks Causing Disturbance | 738 |  | *Private Conflict* | |  | Violent Restraining Order | 950 |
| Panhandler | 555 |  | Breaking/Entering in Progress | 1384 |  |  |  |
| Sex Offense/Lewd Behavior | 639 |  | Domestic Violence Intimate/Partner | 4779 |  |  |  |
|  |  |  |  |  |  |  |  |
| **Violent Crime** | | | | | | | |
| *Public Violence* | |  | Emotionally Disturbed Person: Violent or Injured | 5675 |  | *Prevalence of Guns* | |
| Assault and Battery in Progress | 2100 |  | Fight | 4511 |  | Assault and Battery with Deadly Weapon | 83 |
| Assault and Battery Report | 1487 |  | Person with Knife | 671 |  | Person with a Gun | 613 |
| Armed Robbery | 343 |  |  |  |  | Shots | 609 |
|  |  |  |  |  |  | Person Shot | 420 |

PWD – Public Works Department

*Note:* Any discrepancy with the counts reported in O’Brien and Winship (\_\_\_) is a consequence of the new Geographical Infrastructure, which led to the omission of some cases whose location was no longer maintained by the City.

**Table 2.** Characteristics of addresses, streets, and tracts in Boston.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Mean (SD or Range)**  **or Count (%)** |  |  | **Mean (SD or Range)**  **or Count (%)** | |
| **Addresses (*n* = 98,355)** | | | | | |
| Number of Units | 2.25 (6.11) |  |  | |  |
| *Land Usage* | | | | | |
| Apartment | 2,456 (2%) |  | Industrial | | 354 (<1%) |
| Commercial | 3,860 (4%) |  | Residential: Single-Family | | 30,353 (31%) |
| Commercial Condo | 91 (<1%) |  | Residential: Two-Family | | 17,268 (18%) |
| Condominium | 8,574 (9%) |  | Residential: Three-Family | | 13,832 (14%) |
| Commercial Lot | 2,048 (2%) |  | Residential: Four-Family | | 2,505 (3%) |
| Condo Parking | 114 (<1%) |  | Residential-Commercial | | 2,485 (2%) |
| Exempta | 7,215 (7%) |  | Residential Lot | | 6,714 (7%) |
| Exempt (Chapter 121A)a | 455 (<1%) |  |  | |  |
|  |  |  |  | |  |
| **Street Segments (*n* = 13,048)** | | | | | |
| Length | 95.33 m  (68.00 m) |  | Number of Addresses | 7.46 (7.83) | |
| Main Street | 3,577 (27%) |  |  |  | |
| *Predominant Zoning* | | | | | |
| Three-Family Residential with Assorted Other Uses | 3,136 (24%) |  | Exempt | 1,346 (10%) | |
| Mix of Two-Family and Single-Family Residential | 2,232 (17%) |  | Condominiums | 1,244 (10%) | |
| Commercial | 1,298 (10%) |  | Mixed-Use Commercial | 553 (4%) | |
| Single-Family Residential Only | 3,239 (25%) |  |  |  | |
|  |  |  |  |  | |
| **Census Tracts (*n* = 178)** | | | | | |
| Total Population | 3,466 ppl. (1,556 ppl.) |  | Households | 1,531 units  (717 units) | |
| *Neighborhood Type* | | | | | |
| Downtown | 12 (7%) |  | Parks | 14 (8%) | |
| Industrial/ Institutionalb | 31 (17%) |  | Residential | 121 (68%) | |

a – Buildings owned by government, and non-profits are tax exempt. In addition, Chapter 121A establishes subsidized housing as tax exempt.

b – Includes regions dominated by institutional uses, including industrial zones, colleges and universities, and travel hubs (e.g., the airport).

**Table 3.** Total number of events for the six categories of crime and disorder and their distribution across addresses, streets, and census tracts.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **Addresses** | | |  | | **Streets** | | |  | **Tracts** | | |
|  | **Total** | **Mean (SD)** | **Range** | ***G’***  **(E(G’))** | |  | **Mean (SD)** | **Range** | ***G’* (E(G’))** |  | **Mean (SD)** | **Range** | ***G’* (E(G’))** | |
| *Private Neglect* | 9,072 | 0.09 (0.68) | 0-47 | .73 (.09) | |  | 0.69 (2.17) | 0-52 | .84 (.43) |  | 50.71 (43.56) | 0-226 | .46 (.08) | |
| *Public Denigration* | 6,201 | 0.06 (0.48) | 0-60 | .52  (.06) | |  | 0.47 (1.71) | 0-60 | .76 (.33) |  | 34.64 (35.86) | 0-199 | .51 (.10) | |
| *Public Social Disorder* | 3,498 | 0.04 (0.47) | 0-62 | .61  (.03) | |  | 0.27 (1.45) | 0-62 | .73 (.22) |  | 19.44 (21.90) | 0-171 | .51 (.13) | |
| *Private Conflict* | 11,187 | 0.11 (0.63) | 0-40 | .55 (.10) | |  | 0.85 (2.05) | 0-40 | .77 (.48) |  | 62.35 (51.30) | 0-255 | .44 (.07) | |
| *Public Violence* | 14,788 | 0.15 (1.09) | 0-81 | .76 (.13) | |  | 1.11 (3.30) | 0-81 | .85 (.50) |  | 81.87 (63.83) | 0-412 | .41 (.06) | |
| *Prevalence of Guns* | 1,725 | 0.02 (0.20) | 0-25 | .43 (.02) | |  | 0.13 (0.60) | 0-25 | .56 (.12) |  | 9.59 (11.13) | 0-48 | .58 (.18) | |

**Table 4.** Gini coefficients quantifying the equality of the distribution of crime and disorder across addresses on streets, streets in tracts, and tracts in the city compared to expected values, both ignoring and accounting for aspects of urban form.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Addresses w/in streets** | | |  | **Streets w/in tracts** | | | | |
|  | **Raw counts** | **Address Controls** | **E(G’) (*n*a)** |  | **Raw counts** | **Address Controls** | **Street Controls** | **# of Addresses** | **E(G’) (*n*a)** |
| *Private Neglect* | .73 | .72 | .31 (310) |  | .70 | .70 | .70 | .62 | .35 (156) |
| *Public Denigration* | .61 | .61 | .34 (150) |  | .51 | .51 | .51 | .44 | .27 (154) |
| *Public Social Disorder* | .73 | .73 | .37 (45) |  | .50 | .50 | .50 | .46 | .24 (137) |
| *Private Conflict* | .63 | .61 | .31 (286) |  | .60 | .59 | .60 | .48 | .36 (166) |
| *Public Violence* | .72 | .72 | .35 (379) |  | .70 | .69 | .69 | .68 | .37 (167) |
| *Prevalence of Guns* | .66 | .66 | .32 (25) |  | .41 | .41 | .41 | .39 | .17 (99) |

a – The number of streets or tracts containing 5 or more addresses or streets, respectively, and experiencing 5 or more events of the given category (expect for Prevalence of Guns, for which the thresholds are 4 and 4).

**Table 4 (Cont).**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Tracts in City** | | | | | |
|  | **Raw counts** | **Address Controls** | **Street Controls** | **Tract Controls** | **# of Addresses and Streetsb** | **E(G’)** |
| *Private Neglect* | .46 | .46 | .46 | .46 | .25 | .08 |
| *Public Denigration* | .51 | .51 | .51 | .50 | .38 | .10 |
| *Public Social Disorder* | .51 | .51 | .51 | .51 | .31 | .12 |
| *Private Conflict* | .44 | .43 | .43 | .43 | .28 | .07 |
| *Public Violence* | .41 | .41 | .41 | .41 | .30 | .06 |
| *Prevalence of Guns* | .58 | .58 | .58 | .58 | .35 | .16 |

b – Calculated by summing the number of events above expected across all streets controlling for the number of addresses on each street in a census tract and then estimating how far above or below this sum was based on the number of streets in the tract.

**Appendix**

**Table A1.** Regression estimates of the influence of number of addresses on a street and number of events distributed across those addresses on Gini coefficients for streets for a) analysis of raw counts and b) counts above expected based on address features.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Private Neglect** | |  | **Public Denigration** | |  | **Public Social Disorder** | |  | **Private Conflict** | |  | **Violence** | |  | **Guns** | |
|  | **Raw Count** | **Add. Cntrls.** |  | **Raw Count** | **Add. Cntrls.** |  | **Raw Count** | **Add. Cntrls.** |  | **Raw Count** | **Add. Cntrls.** |  | **Raw Count** | **Add. Cntrls.** |  | **Raw Count** | **Add. Cntrls.** |
| *Events* | .28\*\*\* | .29\*\*\* |  | .28\*\*\* | .29\*\*\* |  | .14 | .14 |  | .33\*\*\* | .33\*\*\* |  | .24\*\*\* | .25\*\*\* |  | .27 | .27 |
| *Adds.* | -.22\*\*\* | -.23\*\*\* |  | -.33\*\*\* | -.33\*\*\* |  | -.30\* | -.30\* |  | -.46\*\*\* | -.45\*\*\* |  | -.38\*\*\* | -.39\*\*\* |  | -.26 | -.26 |
| **Adj. *R*2** | .11 | .11 |  | .18 | .19 |  | .06 | .06 |  | .28 | .27 |  | .21 | .22 |  | .06 | .06 |

**Table A2.** Regression estimates of the influence of number of streets in a tract and number of events distributed across those streets on Gini coefficients for streets for a) analysis of raw counts b) counts above expected based on address features, c) counts above expected based on street features, and d) counts above expected based on number of addresses on a street

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Private Neglect** | | | |  | **Public Denigration** | | | |  | **Public Social Disorder** | | | |
|  | **Raw Count** | **Add. Cntrls.** | **Street Cntrls.** | **# of Adds.** |  | **Raw Count** | **Add. Cntrls.** | **Street Cntrls.** | **# of Adds.** |  | **Raw Count** | **Add. Cntrls.** | **Street Cntrls.** | **# of Adds.** |
| Events | .37\*\*\* | .38\*\*\* | .38\*\*\* | .48\*\*\* |  | .53\*\*\* | .53\*\*\* | .53\*\*\* | .59\*\*\* |  | .62\*\*\* | .62\*\*\* | .62\*\*\* | .64\*\*\* |
| Streets | -.09 | -.09 | -.09 | -.14 |  | -.12 | -.13 | -.13 | -.17\* |  | -.18\*\* | -.19\*\* | -.19\*\* | -.19\*\* |
| **Adj. *R*2** | .12 | .12 | .12 | .21 |  | .28 | .28 | .28 | .35 |  | .38 | .38 | .38 | .40 |

**Table A2 (Cont.).**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Private Conflict** | | | |  | **Violence** | | | |  | **Guns** | | | |
|  | **Raw Count** | **Add. Cntrls.** | **Street Cntrls.** | **# of Adds.** |  | **Raw Count** | **Add. Cntrls.** | **Street Cntrls.** | **# of Adds.** |  | **Raw Count** | **Add. Cntrls.** | **Street Cntrls.** | **# of Adds.** |
| Events | .41\*\*\* | .43\*\*\* | .43\*\*\* | .58\*\*\* |  | .24\*\* | .26\*\* | .26\*\* | .41\*\*\* |  | .58\*\*\* | .58\*\*\* | .58\*\*\* | .59\*\*\* |
| Streets | -.22\*\* | -.24\*\* | -.23\*\* | -.29\*\*\* |  | -.03 | -.04 | -.05 | -.16\* |  | -.23\*\* | -.23\*\* | -.23\*\* | -.23\*\* |
| **Adj. *R*2** | .15 | .17 | .16 | .30 |  | .04 | .05 | .05 | .15 |  | .37 | .37 | .37 | .37 |

**Table A3.** Complete parameter estimates from multilevel models predicting counts of reports of crime and disorder based on characteristics of the address, street, and census tract.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **Private Neglect** | |  | **Public Denigration** | | | | | | | | |  | | | | **Public Social Disorder** | | |  | | **Private Conflict** | | | |  | | | **Public Violence** | | | |  | | | | **Prevalence of Guns** | | | |
|  |  | **Beta (Std. Error)** | **Odds Ratio** |  | **Beta (Std. Error)** | | | | | **Odds Ratio** | |  | | | **Beta (Std. Error)** | | | | **Odds Ratio** | |  | | **Beta (Std. Error)** | | **Odds Ratio** | |  | | **Beta (Std. Error)** | | | **Odds Ratio** | |  | | | **Beta (Std. Error)** | | | **Odds Ratio** | | | |
| Address Characteristics | | | | | | | |
| *Land Usage*a |  |  |  |  | |  | | | |  | |  | | |  | | | |  | |  | |  | |  | |  | |  | | |  | |  | | |  | | |  | | | |
| Apartment |  | 2.82\*\*\* (0.06) | 16.72 |  | | 1.31\*\*\* (0.05) | | | | 3.72 | |  | | | 1.66\*\*\* (0.07) | | | | 5.28 | |  | | 2.21\*\*\* (0.05) | | 9.22 | |  | | 2.18\*\*\* (0.06) | | | 8.87 | |  | | | 1.24\*\*\* (0.06) | | | 3.43 | | | |
| Commercial |  | 0.13 (0.11) | 1.14 |  | | 1.31\*\*\* (0.06) | | | | 3.71 | |  | | | 1.83\*\*\* (0.06) | | | | 6.23 | |  | | 0.77\*\*\* (0.07) | | 2.15 | |  | | 1.80\*\*\* (0.05) | | | 6.04 | |  | | | 1.01\*\*\* (0.07) | | | 2.74 | | | |
| Commercial Condo |  | -0.34 (0.42) | 0.71 |  | | 1.81\*\*\* (0.14) | | | | 6.10 | |  | | | 2.18\*\*\* (0.10) | | | | 8.86 | |  | | 1.13\*\*\* (0.21) | | 3.10 | |  | | 1.57\*\*\* (0.13) | | | 4.79 | |  | | | 1.14\*\*\* (0.22) | | | 3.12 | | | |
| Condominium |  | 1.58\*\*\* (0.06) | 4.86 |  | | 0.87\*\*\* (0.05) | | | | 2.39 | |  | | | 1.22\*\*\* (0.06) | | | | 3.38 | |  | | 1.29\*\*\* (0.05) | | 3.62 | |  | | 0.90\*\*\* (0.06) | | | 2.45 | |  | | | 0.80\*\*\* (0.06) | | | 2.23 | | | |
| Commercial Lot |  | -0.79\*\*\* (0.19) | 0.46 |  | | -0.15 (0.11) | | | | 0.86 | |  | | | -0.96\*\*\* (0.13) | | | | 0.38 | |  | | -1.12\*\*\* (0.15) | | 0.32 | |  | | -0.34\*\* (0.11) | | | 0.71 | |  | | | -1.97\*\*\* (0.22) | | | 0.14 | | | |
| Exempt |  | 0.99\*\*\* (0.07) | 2.69 |  | | | 0.69\*\*\* (0.06) | | | | 2.00 | | |  | | | 1.28\*\*\* (0.06) | | | 3.60 | |  | | .69\*\*\* (0.06) | | 2.00 | |  | | | 1.74\*\*\* (0.05) | | 5.72 | | |  | | 0.56\*\*\* (0.06) | | | 1.75 | | | |
| Exempt (121A) |  | 2.24\*\*\* (0.13) | 9.44 |  | | | 0.58\*\*\* (0.14) | | | | 1.78 | | |  | | | 1.79\*\*\* (0.12) | | | 5.99 | |  | | 1.94\*\*\* (0.10) | | 6.97 | |  | | | 1.81\*\*\* (0.10) | | 6.10 | | |  | | 1.53\*\*\* (0.11) | | | 4.63 | | | |
| Industrial |  | 0.41 (0.30) | 1.50 |  | | | 1.41\*\*\* (0.13) | | | | 4.11 | | |  | | | 0.10 (0.19) | | | 1.10 | |  | | -0.14 (0.22) | | 0.87 | |  | | | 0.49\*\* (0.17) | | 1.64 | | |  | | 0.72\*\* (0.20) | | | 2.06 | | | |
| Residential: Two-Family |  | 1.16\*\*\* (0.05) | 3.19 |  | | | 0.33\*\*\* (0.05) | | | | 1.39 | | |  | | | 0.47\*\*\* (0.06) | | | 1.60 | |  | | 0.73\*\*\* (0.04) | | 2.08 | |  | | | 0.38\*\*\* (0.05) | | 1.47 | | |  | | 0.35\*\*\* (0.05) | | | 1.42 | | | |
| Residential: Three-Family |  | 1.79\*\*\* (0.05) | 6.00 |  | | | 0.73\*\*\* (0.05) | | | | 2.08 | | |  | | | 0.70\*\*\* (0.06) | | | 2.00 | |  | | 1.24\*\*\* (0.04) | | 3.46 | |  | | | 0.94\*\*\* (0.05) | | 2.57 | | |  | | 0.60\*\*\* (0.05) | | | 1.82 | | | |
| Residential: Four-Family |  | 2.41\*\*\* (0.06) | 11.18 |  | | | 1.03\*\*\* (0.05) | | | | 2.81 | | |  | | | 1.13\*\*\* (0.08) | | | 3.08 | |  | | 1.77\*\*\* (0.06) | | 5.85 | |  | | | 1.36\*\*\* (0.06) | | 3.90 | | |  | | 0.93\*\*\* (0.07) | | | 2.53 | | | |
| Residential-Commercial |  | 2.12\*\*\* (0.07) | 8.33 |  | | | 1.33\*\*\* (0.06) | | | | 3.78 | | |  | | | 1.41\*\*\* (0.06) | | | 4.08 | |  | | 1.72\*\*\* (0.06) | | 5.58 | |  | | | 1.78\*\*\* (0.06) | | 5.94 | | |  | | 1.25\*\*\* (0.07) | | | 3.48 | | | |
| Residential Lot |  | -0.24\* (0.09) | 0.79 |  | | | -1.08\*\*\* (0.11) | | | | 0.34 | | |  | | | -3.04\*\*\* (0.33) | | | 0.05 | |  | | -2.13\*\*\* (0.16) | | 0.12 | |  | | | -2.05\*\* (0.17) | | 0.13 | | |  | | -1.60\*\*\* (0.11) | | | 0.20 | | | |
| *# of Units* |  | 0.017\*\*\* (0.001) | 1.02 |  | | | 0.009\*\*\* (0.001) | | | | 1.01 | | |  | | | 0.008\*\*\* (0.001) | | | 1.01 | |  | | 0.012\*\*\* (0.001) | | 1.01 | |  | | | 0.015\*\*\* (0.001) | | 1.01 | | |  | | 0.016\*\*\* (0.001) | | | 1.02 | | | |
| Street Characteristics | | | | | | | | |
| *Length*b |  | 0.14\*\* (0.04) | 1.15 |  | | | 0.01 (0.04) | | | | 1.01 | | |  | | | 0.15\* (0.06) | | | 1.17 | |  | | 0.23\*\*\* (0.03) | | 1.27 | |  | | | 0.29\*\*\* (0.03) | | 1.34 | | |  | | 0.31\*\*\* (0.07) | | | 1.36 | | | |
| *# Parcels* |  | -0.02\*\*\* (.003) | 0.98 |  | | | -0.01\*\*\* (.003) | | | | 0.99 | | |  | | | -0.03\*\*\* (.005) | | | 0.97 | |  | | -0.03\*\*\* (0.003) | | 0.97 | |  | | | -.03\*\*\* (0.003) | | 0.97 | | |  | | -.04\*\*\* (0.007) | | | 0.97 | | | |
| *Main Street*c |  | 0.31\*\*\* (0.05) | 1.36 |  | | | 0.27\*\*\* (0.05) | | | | 1.31 | | |  | | | 0.74\*\*\* (0.07) | | | 2.10 | |  | | 0.25\*\*\* (0.04) | | 1.28 | |  | | | 0.50\*\*\* (0.04) | | 1.65 | | |  | | 0.54\*\*\* (0.09) | | | 1.72 | | | |
| *Land Usage*d |  |  |  |  | | |  | | | |  | | |  | | |  | | |  | |  | |  | |  | |  | | |  | |  | | |  | |  | | |  | | | |
| 3-Family Mixed |  | 0.31\*\*\* (0.08) | 1.36 |  | | | 0.35\*\*\* (0.08) | | | | 1.42 | | |  | | | 0.60\*\*\* (0.12) | | | 1.82 | |  | | 0.24\*\*\* (0.06) | | 1.28 | |  | | | 0.51\*\*\* (0.07) | | 1.67 | | |  | | 0.96\*\*\* (0.14) | | | 2.61 | | | |
| 2-Family w/ single-family |  | 0.17\* (0.08) | 1.18 |  | | | 0.14 (0.08) | | | | 1.15 | | |  | | | 0.24 (0.12) | | | 1.27 | |  | | 0.11 (0.06) | | 1.11 | |  | | | 0.40\*\*\* (0.07) | | 1.49 | | |  | | 0.29\* (0.15) | | | 1.34 | | | |
| Pure Commercial |  | 0.22 (0.13) | 1.25 |  | | | 0.45\*\*\* (0.11) | | | | 1.56 | | |  | | | 1.25\*\*\* (0.14) | | | 3.48 | |  | | 0.65\*\*\* (0.08) | | 1.92 | |  | | | 0.64\*\*\* (0.09) | | 1.90 | | |  | | 1.12\*\*\* (0.19) | | | 3.07 | | | |
| Exempt |  | 0.23 (0.12) | 1.26 |  | | | 0.04 (0.11) | | | | 1.04 | | |  | | | 0.55\*\*\* (0.15) | | | 1.73 | |  | | 0.41\*\*\* (0.08) | | 1.50 | |  | | | 0.12 (0.09) | | 1.13 | | |  | | 1.12\*\*\* (0.18) | | | 3.06 | | | |
| Condominiums |  | 0.09 (0.10) | 1.09 |  | | | 0.53\*\*\* (0.09) | | | | 1.71 | | |  | | | 0.24 (0.14) | | | 1.28 | |  | | -0.11 (0.07) | | 0.89 | |  | | | 0.14 (0.09) | | 1.15 | | |  | | -0.12 (0.20) | | | 0.88 | | | |
| Mixed Commercial |  | 0.50\*\*\* (0.13) | 1.65 |  | | | 0.63\*\*\* (0.12) | | | | 1.87 | | |  | | | 1.25\*\*\* (0.16) | | | 3.49 | |  | | 0.31\*\* (0.09) | | 1.36 | |  | | | 0.66\*\*\* (0.10) | | 1.94 | | |  | | 0.95\*\*\* (0.21) | | | 2.60 | | | |
| Tract Characteristics | | | | | | | | |
| *Total Pop. (1,000s)* |  | 0.21\*\*\* (0.06) | 1.24 |  | | | -0.21\*\* (0.06) | | | | 0.81 | | |  | | | 0.02 (0.06) | | | 1.02 | |  | | 0.19\*\*\* (0.05) | | 1.21 | |  | | | 0.12\* (0.05) | | 1.13 | | |  | | 0.36\*\* (0.10) | | | 1.43 | | | |
| *Total Households (100s)* |  | -0.03\* (0.01) | 0.97 |  | | | 0.06\*\*\* (0.01) | | | | 1.06 | | |  | | | 0.01 (0.01) | | | 1.01 | |  | | -0.03\*\* (0.01) | | 0.97 | |  | | | -0.01 (0.01) | | 0.99 | | |  | | -0.08\*\* (0.02) | | | 0.92 | | | |
| *Nbhd Type*e |  |  |  |  | | |  | | | |  | | |  | | |  | | |  | |  | |  | |  | |  | | |  | |  | | |  | |  | | |  | | | |
| Downtown |  | -0.81\*\*\* (0.22) | 0.45 |  | | | 0.48\* (0.22) | | | | 1.62 | | |  | | | 0.26 (0.22) | | | 1.30 | |  | | -0.18 (0.18) | | 0.83 | |  | | | -0.04 (0.19) | | 0.96 | | |  | | -0.65 (0.39) | | | 0.52 | | | |
| Institutional |  | -0.10 (0.13) | 0.91 |  | | | 0.46\*\* (0.15) | | | | 1.58 | | |  | | | 0.22 (0.15) | | | 1.25 | |  | | -0.12 (0.12) | | 0.89 | |  | | | -0.08 (0.12) | | 0.92 | | |  | | -0.66\*\* (0.24) | | | 0.52 | | | |
| Park |  | 0.04 (0.21) | 1.05 |  | | | -0.33 (0.25) | | | | 0.72 | | |  | | | -0.25 (0.25) | | | 0.78 | |  | | 0.15 (0.18) | | 1.16 | |  | | | -0.13 (0.19) | | 0.87 | | |  | | -0.28 (0.38) | | | 0.76 | | | |
| **N (roads/tracts)** |  | **97,287 (13,045/178)** | |  | | | **97,287 (13,045/178)** | | | | | |  | | | **97,287 (13,045/178)** | | | | | |  | | **97,287 (13,045/178)** | | | |  | | | **97,287 (13,045/178)** | | | |  | | | | **97,287 (13,045/178)** | | | |

*Note: N* = 123,265 addresses nested in 13,767 street segments in 178 census tracts.

a-A series of dichotomous variables reflecting an address’ land usage, with Residential: Single-Family acting as the reference group. Parameters were not estimated for two land uses with very few addresses (Agricultural and Condo Parking).

b-100s of meters.

c- A dichotomous variable with ‘1’ equal to variable name.

d- A series of dichotomous variables reflecting a street’s predominant land usage, based on a cluster analysis of land use types (\_\_\_\_). Single-Family Residential is the reference group.

e- A series of dichotomous variables reflecting a tract’s predominant usage, with Residential acting as the reference group.

\* - *p* < .05, \*\* - *p* < .01, \*\*\* - *p* < .001

1. Separate reports referring to the same issue were removed based on a common case enquiry ID that is maintained by the 311 system administrators. [↑](#footnote-ref-1)
2. For 311, all reports are attributed to a known address, as constrained by the input system’s usage of a street and address management (SAM) system, at the time of receipt. For 911, addresses are immediately geocoded to the same SAM by municipal servers. There may of course still be errors in the determination of the nearest address at the time of the report, but these safeguards make us confident that few if any additional errors are introduced during data processing. [↑](#footnote-ref-2)
3. Readers will note that these numbers differ somewhat from O’Brien & Winship (\_\_\_), which uses the same basic database and analytic structure. The 2017 update of the Boston Area Research Initiative’s Geographical Infrastructure of Boston transitioned from an outdated definition of “addresses” to the focus on properties and land parcels described here. This resulted in fewer land parcels than addresses and the analytic exclusion of a handful of street segments with no meaningful land uses (typically very short segments). [↑](#footnote-ref-3)
4. Given that some street segments form the border between two tracts, rather than lying clearly inside one or another, the Geographical Infrastructure links each street to the single tract containing its centroid. For street segments that are part of the border between two tracts, this process assigns them randomly to one, limiting any systematic bias in the subsequent analyses. To maintain perfect three-level nesting, addresses on a street segment that crossed over two or more tracts were attributed to the tract within which the centroid of that street segment lies and not necessarily the tract containing the address. [↑](#footnote-ref-4)
5. As warned by Bernasco and Steebeek (2017), traditional Gini coefficients ranged from .95-.99 at the address level and .82-.94 for streets. [↑](#footnote-ref-5)
6. It is feasibly possible to compare the significance of these differences using bootstrapping, but all of the Gini estimates had a standard error <.001, making nearly any measureable difference a “significant” effect. [↑](#footnote-ref-6)
7. Comparison to the global analysis of tracts is a little less exact, however, as there are 178 tracts and far more events than linked to any single street or tract, though these values are far outside the reasonable range for estimating concentrations at the other levels. [↑](#footnote-ref-7)
8. Also worth noting, there was a consistent arithmetic relationship between the number of events, the number of units, and the estimated Gini coefficients; concentrations tended to be higher with a greater volume of events and lower with a greater number of units to spread the events across. [↑](#footnote-ref-8)
9. Parameters were drawn from multilevel models comparing addresses on the same street, thereby isolating address-level effects. The count of events above expected was then the number of events minus the expected number of events. Because many addresses had zero events in one or more categories, this number could feasibly be negative. In all such cases we reset the value to zero. [↑](#footnote-ref-9)