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The Gains of Greater Granularity: The Presence and Persistence of Problem Properties in Urban Neighborhoods

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Abstract
Objectives This study applies the growing emphasis on micro-places to the analysis of addresses, assessing the presence and persistence of "problem properties" with elevated levels of crime and disorder. It evaluates what insights this additional detail offers beyond the analysis of neighborhoods and street segments.
Methods We used over 2,000,000 geocoded emergency and non-emergency requests received by the City of Boston's 911 and 311 systems from 2011–2013 to calculate six indices of violent crime, physical disorder, and social disorder for all addresses (n = 123,265). We linked addresses to their street segment (n = 13,767) and census tract (n = 178), creating a three-level hierarchy that enabled a series of multilevel Poisson hierarchical models.
Results Less than 1% of addresses generated 25% of reports of crime and disorder. Across indices, 95–99% of variance was at the address level, though there was significant clustering at the street segment and neighborhood levels. Models with lag predictors found that levels of crime and disorder persisted across years for all outcomes at all three geographic levels, with stronger effects at higher geographic levels. Distinctively, ~15% of addresses generated crime or disorder in one year and not in the other.
Conclusions The analysis suggests new opportunities for both the criminology of place and the management of public safety in considering addresses in conjunction with higher-order geographies. We explore directions for empirical work including the further experimentation with and evaluation of law enforcement policies targeting problem properties.

Keywords Law of concentration of crime · Physical disorder · Social disorder · Violent crime · Computational social science

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Introduction

One of the fundamental inspirations for urban criminology is the uneven distribution of crime across space. As early as Booth's (1903) mapping of the physical and social conditions of the streets of London, it has been apparent that some parts of the city suffer from high concentrations of crime, whereas many others experience little to none. Historically, research in this vein has concentrated on neighborhoods and the social and behavioral dynamics that lead to the emergence of high- and low-crime areas (e.g., Shaw and McKay 1942/1969; Sampson et al. 1997; Wilson and Kelling 1982). Over the past 20 years, however, there has been an effort to examine crime concentrations at increasingly fine spatial resolutions (e.g., Weisburd 2015; Braga et al. 2010; Curman et al. 2015; Smith et al. 2000; Eck and Weisburd 1995a, b; Weisburd et al. 2012), most notably the street segment, with important implications for both theory and policy. Work in this vein has revealed that many "good" neighborhoods contain streets with high concentrations of crime, and that many of the street blocks in "bad" neighborhoods are actually quite safe. This has inspired new theorizing on the "criminology of place," and the structural, behavioral, and social dynamics that are responsible for crime concentrations (Weisburd 2012; Sherman et al. 1989; Eck and Weisburd 1995a, b; Weisburd 2015). It has also led to innovations in "hotspot policing" that refocus patrols on streets and intersections known to generate high levels of crime (Braga and Bond 2008; Weisburd et al. 2011; Weisburd and Amram 2014).

Policymakers in a handful of American cities have sought to take this analysis of crime at micro-places one step further, identifying and combatting "problem properties" (e.g., Minneapolis 2016; LISC 2016; Way et al. 2013; Boston 2011). High-quality digital data and new laws have enabled municipalities to target the owners of properties that generate excessive amounts of crime and disorder, a strategy that is supported by a number of existing studies, including early work on the concentration of crime and disorder at addresses (e.g., Sherman et al. 1989; Pierce et al. 1988; Eck 1994), as well as the extensive literature on the repeat victimization of individuals and properties (e.g., Farrell and Pease 2001; Johnson et al. 2007; Trickett et al. 1992). These insights, however, have not been fully integrated with current methodological and theoretical approaches to the criminology of place. Our goal here is to help bridge this gap in order to evaluate how much is gained by embracing this finer level of granularity.

The current study examines 3 years of requests for emergency and non-emergency services (i.e., 911 and 311 reports) from Boston, MA, the same data that inform the operations of the City's Problem Properties Task Force. We focus on three particular areas of interest in order to integrate the study of addresses with current literature on the criminology of place. First, research on repeat victimization has largely focused on crimes against persons and properties, like burglaries and robberies, with less attention to the concentration of cases of disorder and public violence (though see work on shootings; Ratcliffe and Rengert 2008; Youstin et al. 2011; Wells et al. 2012). We expand this to a broad set of indicators of crime and physical and social disorder. Second, repeat victimization is typically analyzed at short time scales (e.g., 1–2 weeks), whereas work in criminology of place has been more concerned with long-term persistence (e.g., years, decades). The current study is the first we know of to apply this latter perspective to addresses. Third, building on the other two, we quantitatively assess the extent to which the concentration and persistence of crime and disorder at the address level is greater than would be expected based on clustering at the streets and neighborhood levels. Further, we conduct initial tests of how patterns at each of these levels of geography might reinforce each other.

Before proceeding to the presentation of data and analyses, the next three sections: (1) review the existing literature on the criminology of place; (2) summarize existing knowledge on the distribution of crime across addresses, with particular attention to the work on repeat victimization; and (3) synthesize these literatures and their methodologies to set up the current study.

Previous Research: Concentrations of Crime

At a time when urban criminology's interest in geographic variations in crime focused on "neighborhoods," often operationalized as census tracts, Sherman et al. (1989) found that 3.3% of addresses accounted for 50% of police dispatches for crime events in Minneapolis, MN. This seminal study ratified a then-recent report by Pierce et al. (1988) that showed that 3.6% of addresses in Boston, MA generated 50% of emergency calls to police. Later, Weisburd et al. (2004) found that over a 14-year period 4.5% of street segments in Seattle accounted for 50% of crime incidents. Subsequent work on "micro-places" has replicated and extended these early findings such that Weisburd (2015) has proposed 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.

The high concentration of crime at micro-places, particularly "hotspot" street segments, has now been demonstrated in multiple cities, including Seattle, Vancouver, Boston, Cincinnati, Tel Aviv-Yafo, New York, and Sacramento (Weisburd 2015; Curman et al. 2015; Braga et al. 2010, 2011; Andresen and Malleson 2011; Weisburd and Amram 2014). Across these studies, 4–6% of streets in a large city generate 50% of crime events; in smaller cities the ratio is even more dramatic, with 2–4% of streets generating 50% of events. Further, this work has demonstrated that the law of concentration of crime is applicable across types of crime. Braga and colleagues have found similar concentrations for gun violence (Braga et al. 2010) and robberies (Braga et al. 2011), and Weisburd et al. (2009) have found even more dramatic concentrations for juvenile arrests.

This body of work has quickly moved beyond the distribution of crime to ask about its persistence over time, noting that it does little to know that crime concentrates at hotspot streets if these hotspots shift from year to year. A handful of studies have sought to address this question by building longitudinal databases of crime at the street level, some covering as much as 30 years. Using statistical techniques that classify street segments with similar cross-time trajectories in their crime levels (e.g., latent growth curve analysis), these studies have consistently identified a small number of street segments (i.e., $\sim$2%) that have stably high levels of crime over time (Groff et al. 2010; Braga et al. 2010, 2011; Curman et al., 2015). Each of these studies has also identified streets with stable, moderate levels of crime, and various forms of increasing or decreasing trajectories. A few have even found volatile trajectories that are consistently elevated but have fluctuated in ways that reflect city-wide crime trends (Braga et al. 2010, 2011). All told, these results provide strong evidence across multiple cities that "hotspots" are not only visible cross-sectionally, but often persist over many years.

A few recent studies on street segments have sought to determine whether focusing on micro-places in fact provides additional knowledge about the distribution of crime, or whether hotspots are just a more granular manifestation of neighborhood-level variations. Curman et al. (2015) found that crime rates persisted more strongly for streets in Vancouver than for dissemination areas (the Canadian equivalent of census block groups) or census tracts. Extending the work on identifying crime trajectories, Groff et al. (2010) examined whether street segments with similar crime trajectories tended to cluster geographically. They found that they did to a degree—most notably in the case of those with high-crime trajectories—but certainly were not segregated by neighborhood. Andresen and Malleson (2011) replicated this finding in Vancouver, providing additional evidence that, at least for these two cities, the study of crime at micro-places generates information that an exclusive focus on neighborhoods does not.

The Concentration of Crime at Addresses

The evidence surrounding the prominence and persistence of hot spots has justified a criminology of place and its value for urban criminology and policing more generally, a paradigmatic shift that Weisburd (2015) has argued has had to overcome an overarching emphasis on individuals and neighborhoods. That said, as this body of work has converged upon the street segment as the optimal unit of analysis, it has opened up the question of whether the law of concentration of crime might be extended to the logical next step: the distribution of crime across addresses. Meanwhile, policymakers in a handful of municipalities have initiated programs that deploy police and other city services to target "problem properties." The goal of this study is to examine the distribution of crime across the addresses of the city, asking the overarching question: What new knowledge does this additional level of granularity afford us?

A considerable literature supports the notion that there is much to be gained from attention to crime at the address level. We noted in the previous section two relevant studies—Sherman et al.'s (1989) seminal analysis of addresses in Minneapolis, MN and Pierce et al.'s (1988) report on addresses in Boston, MA—which are considered early contributions to research on hotspots. Over the last three decades, a parallel line of research has examined the repeat victimization of a single target, be it a person, group, item of property, dwelling, or otherwise (Farrell and Pease 2001; Reiss 1980). A subset of this work has focused on the repeat victimization of addresses, finding strong support for the notion that there is a concentration of crime at the address level that goes beyond that of streets. For instance, Pease (1998) found that 2% of households in the UK accounted for 41% of property crime, and Kleemans (2001) found that 1.2% of the households in the city of Enschede, Netherlands accounted for 25% of burglaries—numbers even more extreme than those found by Weisburd (2015) in his analysis of street segments across multiple cities.

The logic of the repeat victimization literature is twofold. First, many offenders commit multiple crimes in a short period of time, often targeting the same victim or multiple victims in nearby locations (Ashton et al. 1998). Second, some victims have certain traits that make them particularly vulnerable to victimization. This premise has two consequences for the types of question that have been asked in this area. Given the emphasis on "victimization," the work has most heavily concentrated on property crimes, like burglary and auto theft (Bowers and Johnson 2005; Budd 1999; Johnson et al. 2007; Johnson and Bowers 2004; Kleemans 2001; Levy and Tartaro 2010; Townsley et al. 2003), though a handful of studies have extended the logic to shootings (Ratcliffe and Rengert 2008; Wells et al. 2012; Youstin et al. 2011). Temporally, the emphasis of this literature is on how one crime event might raise the likelihood of follow-up events on the very short time scales of days or weeks (e.g., Johnson et al. 2007; Townsley et al. 2003; Bowers and Johnson 2005; Johnson and Bowers 2004; Youstin et al. 2011).

Apart from the empirical evidence the repeat victimization literature provides regarding the concentration of crime at addresses, it also offers useful theoretical tools for understanding this phenomenon. A popular approach for why certain targets become repeat victims entails the identification of "flag" and "boost" factors (Johnson 2008). Flag factors, also known as risk heterogeneity, are characteristics of a target that make them especially vulnerable to crime, like houses that are detached or stand-alone, meaning there are fewer individuals who might observe a break-in (Budd 1999; Bowers and Johnson 2005). Boost factors, also known as event dependence, are any consequences of an initial victimization that increase the likelihood of future victimization; for example, once a property has been burglarized, offenders, including the original perpetrator or perpetrators, will recognize it as a viable future target (Bernasco et al. 2015; Bernasco 2008; Johnson et al. 2009). Though these concepts are explicitly tailored to cases of personal or property crime, there are likely parallels for other forms of crime and disorder (e.g., Wells et al. 2012 do so for shootings).

Another area of common interest is the question of how the occurrence of crime at an address is related to dynamics at higher-order geographic scales. Two findings bear noting. First, the "near repeat" hypothesis posits that an initial crime increases the likelihood of a subsequent crime at a nearby location (Townsley et al. 2003). For example, studies have found that a burglary at one address increases the likelihood of a burglary at a neighboring property in the following month (Bowers and Johnson 2005; Johnson and Bowers 2004; Townsley et al. 2003), and others have found the same for shootings within 1–2 weeks (Youstin et al. 2011; Wells et al. 2012). Given evidence for near repeats across multiple types of crime, in multiple countries (Johnson et al. 2007), one might hypothesize that the street segment will continue to be an important unit of analysis, even if addresses demonstrate additional levels of concentration. Second, studies have shown that repeat victimization is more likely within hotspots and high-crime neighborhoods (Trickett et al. 1995; Bennett 1995; Johnson et al. 1997), suggesting that the characteristics of the broader ecology might reinforce the persistence of crime and disorder at an address. Altogether, this work has been successfully extrapolated for the construction of forecasting models that predict future burglary events, either at a previously victimized property or in the surrounding area (Johnson et al. 2008; Tseloni and Pease 2014; Mohler et al. 2011).

Despite their commonalities, there are important differences between the emphases of research on repeat victimization and the law of concentration of crime. Whereas the former focuses on crimes that have a clear offender and victim, the latter is broader, also including forms of disorder and crime that are symptomatic of a troubled social context, like public drunkenness or fights. The two literatures also attend to different temporal scales. Repeat victimization concentrates on short-term repeats at a particular location, but work on the law of concentration of crime has emphasized the long-term persistence of crime and disorder at micro-places. This study takes a first step in synthesizing these two literatures, applying methodologies typically employed in the study of the concentration and persistence of crime and disorder to the study of addresses, and leveraging theory on repeat victimization to help interpret the findings.

The Current Study: Crime and Disorder at Addresses

The current study examines the distribution of crime and related events (i.e., physical and social disorder) across addresses in Boston, MA using data from 2011–2013 from the City's 311 and 911 systems, which receive and compile requests for non-emergency (e.g., graffiti removal) and emergency (e.g., shooting) government services, respectively. There has been some resistance to the analysis of addresses owing in part to both theoretical and practical arguments against it. Towards the former, Taylor (1997) has described the street segment as a self-contained sociological unit at which behavioral and social routines and processes might reinforce each other, creating a consistent set of characteristics for the space (see also Suttles 1972; Taylor et al. 1984). This very well might be true, but it is an open empirical question if this eliminates the need to differentiate between addresses on the same street because they share a similar likelihood of experiencing crime. Practically, it can be difficult to assign a crime to a specific address and to successfully geocode it, creating a strong potential for measurement error. Advances in modern digital data systems partially allay such concerns, however, as we describe in more detail in the Data and Measures section.

Building on recent work regarding concentrations across crime types, we utilize six different indices of violent crime, physical disorder, and social disorder (two from each category), which were developed through previous work with these two data sources (O'Brien et al. 2015; O'Brien and Sampson 2015). As we analyze the distribution of these indices across addresses, we look to answer the two primary questions that have been central in the study of crime at street segments. The first is *distribution*, or whether crime concentrates at certain addresses in a notable manner over and above its concentration at the street segment or neighborhood level. The second is *persistence*, or whether these localized concentrations are consistent across time. Importantly, we seek not only to measure distribution and persistence for addresses, but to evaluate them relative to the same phenomena at the higher-order levels of streets and neighborhoods, thereby evaluating the extent to which the analysis of addresses provides additional insight on the dynamics of crime across the city. To do so, we utilize multilevel models that nest addresses within streets, and streets within census tracts (Raudenbush and Bryk 2002). These models partition variance among the three geographical levels, thereby measuring the relative concentration of crime within each while accounting for the others. That is to say, the models assess whether concentration of crime at certain addresses can be attributed to clustering at the street or neighborhood level, or, conversely, whether addresses display additional clustering for which the other levels cannot account. This analytic technique has been used in other studies attempting to disentangle variance in the distribution of crime at different geographic levels, though these studies have generally nested either addresses or streets within neighborhoods (e.g., Steenbeek and Weisburd 2016; Schnell et al. 2016; Tseloni 2006); none has examined addresses, streets, and neighborhoods simultaneously, but they all provide preliminary evidence for independent clustering at each of these geographic levels.

A major advantage of multilevel models is the ability to incorporate covariates at all three levels. One opportunity when using longitudinal data is to construct models that use crime in one year to predict crime in the following year. Distinctively, the multilevel framework permits such predictors at all three levels, capturing the strength of persistence at each level on a single measurement scale. A second way that covariates might be utilized is in controlling for elements of the built environment that might influence base rates of crime (e.g., land usage). A major focus of the criminology of place has been on how certain urban forms or locations shape the routine activities and interactions that occur there to give rise to crime hotspots. For example, detached housing attracts more burglaries (e.g., Bowers and Johnson 2005) and street segments with businesses tend to attract more robberies (e.g., Smith et al. 2000). Following this second example, it is notable that studies that have identified the crime level trajectories of streets have found moderate regional concentrations of hotspots, but often in the form of linear clustering along thoroughfares

(Curman et al. 2015; Groff et al. 2010). 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 (e.g., a main street that features lots of businesses). If this is the case, it would be necessary to account for such factors in order to isolate the "true" level of clustering across levels. We leverage additional data describing the addresses, streets, and tracts of Boston for this purpose.

A third advantage of multilevel models is the potential to go beyond the independent assessment of each geographic level to the underexamined area of the interface between them. For example, one consideration in this vein is whether the characteristics of one level (e.g., tract) can moderate the effect of an influential characteristic at a lower level (e.g., address). Previous research has found the repeat victimization is more likely in high-crime neighborhoods and hotspots, suggesting reinforcement at the victim level by the broader context (Trickett et al. 1995; Bennett 1995; Johnson et al. 1997). It is possible to test such questions in multilevel models through cross-level interactions, which we leverage particularly in terms of persistence. From this, it will be possible to know, provided that there is persistence in crime and disorder at the address level, does the level of crime at the street or the tract amplify or dampen the persistence at the address level?

Last, it is important to note that, although the geographically-precise content of calls for service makes them ideal for the study of addresses, they, like other measures of crime based on administrative records, are vulnerable to certain biases introduced by the data-generation process. They do eliminate the potential bias arising from police discretion, inherent to crime reports (Warner and Pierce 1993), but they still depend on the ability and willingness of constituents to report incidences of crime and disorder, and the accuracy with which they describe them. For example, Klinger and Bridges (1997) 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 et al. (2015) 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. Additionally, there is evidence that underreporting obscures the true number of properties suffering from repeat victimization, thereby lowering the estimated level of concentration of crime and disorder (Frank et al. 2012). These limitations should be kept in mind when interpreting the data.

Methods and Data

Data Sources and Measures

The current study utilizes the archive of requests for service received by the City of Boston's 311 system and dispatches made by the 911 system from 2011–2013. For the 311 system, this includes requests received by hotline as well as associated web platforms (e.g., smart phone application). Over this time period the City received 489,900 unique requests through the 311 system[1] and made 1,924,898 911 dispatches. Of these, 457,259 of the 311 requests and 1,790,121 of the 911 dispatches referenced the geographic location where services were to be rendered, reflecting the equivalent of a 93% geocoding rate for both. Data were further limited to those events attributed to an address (i.e., excluding

[1] Duplicates removed using a case enquiry ID that is maintained by the 311 system administrators.

intersections; 369,172 311 reports and 1,673,908 911 dispatches). 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 contained the date and time the request was received.

For Boston's 311 system, all reports were attributed to a known address, as constrained by the input system's usage of a Master Address List, at the time of receipt. For 911, addresses are immediately geocoded to the same Master Address List 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. Further, any pre-data entry errors would likely create measurement error that distributes crime randomly along a street segment, thereby diminishing rather than amplifying the apparent importance of addresses as the unit of analysis.

Previous work with these data 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). 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.

Unit of Analysis

All records were attributed to a known parcel (i.e., the smallest ownable unit), drawn from the Master Address List maintained by the City of Boston. Because some buildings contain more than one parcel (e.g., condominiums), we condensed parcels to 123,265 unique addresses, and tabulated counts for all six categories of disorder and crime for each address for each year. We then constructed a three-level hierarchy of addresses within street segments, and street segments within tracts. We linked addresses to the appropriate street segment in census TIGER Line data ($n = 13{,}767$ segments with addresses), defined as the undivided length of street between two intersections or an intersection and a dead end.

There is an inherent challenge, however, to nesting street segments within census geographies because in many cases they form borders between regions rather than lying clearly inside one or another. To solve this problem we did two things. First, we defined neighborhoods using census tracts ($n = 178$ tracts from the 2010 census), which are sufficiently large that only a small percentage of streets actually compose the borders. Second, we linked 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.[2] The Geographical Infrastructure

[2] 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.

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	74	Unsatisfactory Utilities–Electrical, Plumbing	92
Abandoned building	96	Maintenance complaint–Residential	262		
Bed bugs	379	Mice infestation–residential	400	Public Denigration	
Big buildings enforcement	89	Parking on front/back yards (illegal parking)	121	Abandoned bicycle	53
Big buildings online request	73	Pest infestation–residential	122	Empty litter basket	161
Big buildings resident complaint	60	Poor conditions of property	929	Graffiti removal	2529
Breathe easy	244	Poor ventilation	13	Illegal dumping	706
Chronic dampness/mold	186	Squalid living conditions	43	Improper storage of trash (barrels)	1603
Heat–excessive, insufficient	1035	Trash on vacant lot	116	PWD Graffiti	89
Illegal occupancy	263	Unsatisfactory living conditions	4421	Rodent activity	1207
Illegal rooming house	178				
Lead	56				
Social disorder					
Public social disorder		Vandalism in progress	664	Landlord/tenant trouble	668
Intoxication: individual	1004			Vandalism report	3568
Drunks causing disturbance	774	Private conflict		Violent restraining order	978
Panhandler	584	Breaking/entering in progress	1437		
Sex offense/lewd behavior	674	Domestic violence intimate/partner	4981		
Violent crime					
Public violence		Emotionally disturbed person: violent or injured	5960	Prevalence of guns	
Assault and battery in progress	2216	Fight	4690	Assault and battery with deadly weapon	85
Assault and battery report	1601	Person with knife	694	Person with a gun	635
Armed robbery	353			Shots	631
				Person shot	448

PWD public works department

for the City of Boston, maintained by the Boston Area Research Initiative (https://dataverse.harvard.edu/dataverse/geographical_infrastructure_2015), facilitated this process while also providing information on address land usage (e.g., Residential, Commercial);

the street's length, identification as a Main street (provided by MassGIS), and predominant land usage; the tract's population, number of households, and type (e.g., Residential, Downtown, Park). Table 2 reports descriptive statistics for each of these measures.

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

	Mean (SD or range) or count (%)		Mean (SD or range) or count (%)
Addresses (n = 123,265)			
Total parcels	2.77 (7.28)	Used Parcels	269 (7.17)
Land usage			
Apartment	4,803 (4%)	Industrial	1307 (1%)
Commercial	5,900 (5%)	None	4446 (4%)
Commercial condo	260 (<1%)	Residential: single-family	31,167 (25%)
Condominium	9,876 (8%)	Residential: two-family	22,439 (18%)
Commercial lot	1342 (1%)	Residential: three-family	17,147 (14%)
Condo main	2654 (2%)	Residential: four-family	3772 (3%)
Condo parking	25 (<1%)	Residential-commercial	4735 (4%)
Exempt[a]	8018 (8%)	Residential lot	4081 (3%)
Exempt (Chapter 121A)[a]	1298 (1%)		
Street segments (n = 13,767)			
Length	93.71 m (68.19 m)	Used parcels	24.12 (37.33)
Main Street	3763 (27%)		
Predominant zoning			
Exempt	1466 (11%)	None	288 (2%)
Commercial	1354 (10%)	Residential	9994 (73%)
Industrial	665 (5%)		
Census tracts (n = 178)			
Total population	3466 ppl. (1556 ppl.)	Households	1531 units (717 units)
Neighborhood type			
Downtown	12 (7%)	Parks	14 (8%)
Industrial/ Institutional[b]	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)

Analysis

The main analyses utilized three-level hierarchical models (using HLM 6.06; Raudenbush et al. 2004), nesting addresses within street segments and segments within tracts. This permitted the simultaneous testing of effects at each of these three levels while holding effects at the other levels constant. Each of the models predicted the number of events of a given category at an address. Each of the six outcome variables was a count whose distribution had many zeroes and a long tail (see Results), meaning they violated the primary assumption of a Poisson model (i.e., *mean* $\neq$ *sd*). For this reason we ran Poisson models with a log link with an additional parameter permitting for over- or underdispersion.

Models predicted η_{jkl}, or the natural logarithm of the number of reports generated by the *j*th address on the *k*th street in the *l*th census tract in the form:

$$\eta_{jkl} = \pi_{0kl} + \pi_1 * x_{1jkl} + \ldots + \pi_n * x_{njkl} \quad \text{(Address Equation)}$$

$$\pi_{0kl} = \beta_{00l} + \beta_{01} * x_{(01)kl} + \ldots + \beta_{0n} * x_{(0n)kl} + r_{kl} \quad \text{(Street Equation)}$$

$$\beta_{00l} = \gamma_{000} + \gamma_{001} * x_{(001)l} + \ldots + \gamma_{00n} * x_{(00n)l} + \mu_{0k} \quad \text{(Tract Equation)}$$

where π, β, γ are parameter estimates for predictors at the address, street, and tract levels, respectively, and *r* and μ are error terms at the street and tract levels, respectively. Model predictors included: the address' land use and number of total and currently used parcels; the street's length, identification as a Main street (from MassGIS), predominant land usage, and number of used parcels; and the tract's population, number of households, and type (e.g., Residential, Downtown, Park).

Results

Distribution of Crime and Disorder Across Addresses

The distribution of counts of reports in 2011 indicated considerable concentration of crime and disorder at certain addresses (see Table 3). For all six indices of crime and disorder, no more than 1/10th of addresses had *any* reports; in the case of both forms of physical

Table 3 Distribution of reports of crime and disorder across addresses in 2011

	Mean	Max	# of Non-zeroes	Addresses generating 25% (%)	Addresses generating 50% (%)	Streets generating 50% (%)	Tracts generating 50% (%)
Private neglect	0.07	22	4547 (3.6%)	0.2	0.8	3.9	21
Public denigration	0.05	61	4412 (3.6%)	0.3	1.0	3.5	17
Public social disorder	0.04	62	3084 (2.5%)	0.1	0.6	2.4	19
Private conflict	0.18	27	12,735 (10.3%)	0.7	2.4	6.9	25
Public violence	0.14	81	8437 (6.8%)	0.3	1.2	5.1	24
Prevalence of guns	0.02	18	1715 (1.4%)	0.2	0.5	2.5	17

disorder this proportion was 3.6%, and for gun-related incidents, the least common type of crime, it was 1.4%. In contrast, some addresses had dozens of events of a given type.

A more direct way of assessing concentration of crime is to examine the proportion of addresses responsible for 25 and 50% of events. For all categories of crime and disorder we find that 0.5–2.4% of addresses were responsible for 50% of reports, and that, for all six, less than 1% of addresses were responsible for 25% of reports (see Table 3 for all values). If we sum events across all six indices, 0.9% of addresses were responsible for 25% of all reports of crime and disorder, and 3.4% of addresses were responsible for 50% of all reports. For point of comparison, 50% of reports came from 2.4–6.9% of street segments and 17–24% of census tracts. These values were 8 and 26% for all reports of crime and disorder combined. This would suggest that there is greater concentration of crime and disorder at addresses than would be expected given the distribution across street segments and census tracts. Notably, these concentrations are consistent with those reported by Sherman et al. (1989), Pierce et al. (1988) and Pease (1998) for addresses, as well as those reported by Weisburd (2015) for streets. The same analysis produced nearly identical results for 2012 and 2013 (see Appendix). The most notable differences were a rise in reports of public denigration between 2011 and 2012, and a generalized increase in 911 reports of all types between 2011 and 2012.

Comparing Concentrations at Different Levels: Multilevel Models

Three-level hierarchical Poisson models were estimated to predict counts of all six indices of crime and disorder across addresses, accounting for address, street, and tract characteristics. These models also partitioned the variance between the three levels, enabling an analysis of the level of concentration of events at each (see Table 4 for all parameters).

Because of the many parameters and the six different outcome measures, the results of the models describe various relationships between features of the built environment and the distribution of crime and disorder. These are not the primary focus of the current study and deserve more thorough attention in the future. That said, it is worth summarizing some of the more general patterns.

For addresses, the model treated single-family residences as the reference group for land usage, finding them to generate among the lowest levels of crime and disorder. We see a predictable rise in the number of reports that a residential building is likely to produce as the number of units increases. Non-residential uses, like commercial and exempt (i.e., owned by government or a non-profit, including public housing), are often on the higher end, more comparable in the level of disorder and crime to high-density housing. This is true except in the case of private neglect, which is more specific to residential properties.

At the street level, addresses on main streets and on streets dominated by commercial zoning consistently generated more reports of crime and disorder. In contrast, the neighborhood-level predictors were inconsistent across measures of crime and disorder. Last, one will note in certain models contrasting effects between closely related variables (e.g., a positive effect of population and negative effect of number of households on the prevalence of guns at an address in a given tract). These cases should be interpreted cautiously if at all as the collinear predictors were included in the models together only for the purpose of creating comprehensive models, and not necessarily for substantive hypothesis testing.

All six models found significant clustering of disorder and crime at the street and tract levels (all p values $<.001$), however the actual proportion of variation that these higher levels accounted for was quite small. Across outcomes, 0.8–4% of variance was at the street level and 0.1–1% of variance was at the tract level. Consequently, between 95 and

Table 4 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 (SE)	Odds ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds ratio
Address characteristics												
Land usage[a]												
Apartment	2.14*** (0.06)	8.46	0.80*** (0.05)	2.23	0.72*** (0.06)	2.05	1.56*** (0.04)	4.74	1.46*** (0.05)	4.32	0.63*** (0.06)	1.87
Commercial	−0.03 (0.11)	0.97	0.77*** (0.05)	2.15	1.11*** (0.05)	3.03	0.38*** (0.06)	1.47	1.37*** (0.05)	3.92	0.53*** (0.06)	1.70
Condominium	1.24*** (0.06)	3.45	0.49*** (0.05)	1.64	0.81*** (0.05)	2.24	1.03*** (0.04)	2.80	0.91*** (0.05)	2.49	0.69*** (0.05)	1.99
Commercial Lot	−0.37 (0.20)	0.69	0.23* (0.10)	1.25	0.33** (0.10)	1.39	−0.35** (0.12)	0.70	0.59** (0.09)	1.80	−0.77** (0.16)	0.46
Condo Main	0.44** (0.12)	1.55	0.26*** (0.07)	1.29	0.56*** (0.07)	1.75	0.58*** (0.07)	1.78	0.45*** (0.08)	1.57	−0.33* (0.11)	0.72
Exempt	0.81*** (0.07)	2.25	0.71*** (0.06)	2.03	0.88*** (0.05)	2.42	.52*** (0.05)	1.69	1.59*** (0.04)	4.90	0.21*** (0.06)	1.23
Exempt (121A)	1.42*** (0.11)	4.15	0.30** (0.10)	1.35	0.56** (0.10)	1.74	1.01*** (0.07)	2.74	1.26*** (0.08)	3.51	0.85*** (0.09)	2.33
Industrial	0.42* (0.17)	1.52	0.86*** (0.09)	2.37	0.52*** (0.09)	1.68	0.12 (0.11)	1.13	0.62*** (0.07)	1.85	−0.20 (0.14)	0.82
None	−0.97*** (0.15)	0.38	−0.76*** (0.10)	0.47	−0.28** (0.08)	0.75	−0.48*** (0.08)	0.62	0.05 (0.07)	1.05	−0.63*** (0.08)	0.53
Residential: two-family	1.06*** (0.05)	2.89	0.21*** (0.05)	1.24	0.11* (0.05)	1.12	0.56*** (0.04)	1.75	0.28*** (0.04)	1.32	0.00 (0.05)	1.00
Residential: three-family	1.66*** (0.05)	5.26	0.62*** (0.04)	1.86	0.23*** (0.05)	1.26	1.15*** (0.04)	3.15	0.80*** (0.04)	2.23	0.29*** (0.04)	1.33
Residential: four-family	1.97*** (0.06)	7.19	0.86*** (0.05)	2.35	0.28*** (0.08)	1.32	1.35*** (0.05)	3.84	0.92*** (0.06)	2.51	0.27*** (0.07)	1.31

Table 4 continued

	Private neglect		Public denigration		Public social disorder		Private conflict		Public violence		Prevalence of guns	
	Beta (Std. Error)	Odds Ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds ratio
Residential-commercial	1.25*** (0.08)	3.49	0.67*** (0.05)	1.96	0.40*** (0.05)	1.49	0.91*** (0.05)	2.48	0.93*** (0.05)	2.52	−0.05 (0.08)	0.95
Residential Lot	0.21* (0.09)	1.24	−0.74*** (0.09)	0.48	−0.37*** (0.10)	0.69	−0.78*** (0.09)	0.46	−0.30** (0.09)	0.74	−0.81*** (0.09)	0.45
Parcels	0.019** (0.006)	1.02	0.008 (0.006)	1.01	0.014*** (0.004)	1.01	0.009* (0.004)	1.01	0.004 (0.005)	1.00	0.03*** (0.01)	1.03
Used Parcels	0.004 (0.006)	1.00	0.002 (0.006)	1.00	−0.004 (0.004)	1.00	0.006 (0.004)	1.01	0.009 (0.005)	1.01	−0.02* (0.006)	0.99
Street characteristics												
Length[b]	−0.035 (0.032)	0.97	−0.08* (0.03)	0.92	−0.10* (0.04)	0.91	−0.03 (0.02)	0.97	0.01 (0.02)	1.01	0.02 (0.05)	1.02
Used parcels	.00 (.00)	1.00	.00 (.00)	1.00	.002** (.0006)	1.00	.001 (.0003)	1.00	.00 (.00)	1.00	.00 (.001)	1.00
Main street[c]	0.23*** (0.05)	1.25	0.39*** (0.05)	1.48	0.85*** (0.06)	2.35	0.21*** (0.03)	1.23	0.53*** (0.04)	1.70	0.61*** (0.08)	1.83
Land usage[d]												
Commercial	0.15 (0.09)	1.16	0.18* (0.07)	1.19	0.63*** (0.08)	1.88	0.17** (0.05)	1.18	0.34*** (0.06)	1.40	0.44*** (0.12)	1.56
Industrial	−0.09 (0.18)	0.91	0.12 (0.13)	1.13	−0.09 (0.16)	0.92	0.24* (0.10)	1.27	0.04 (0.11)	1.04	0.24 (0.23)	1.27
Exempt	0.42*** (0.09)	1.52	−0.59*** (0.10)	0.55	0.26*** (0.09)	1.29	0.42*** (0.06)	1.52	0.16* (0.06)	1.17	0.76*** (0.12)	2.14
No Zoning	0.15 (0.09)	1.36	−0.68* (0.28)	0.51	0.25* (0.09)	1.29	0.47*** (0.12)	1.60	0.24 (0.15)	1.27	0.68* (0.29)	1.98
Tract characteristics												
Total Pop. (1,000 s)	0.15* (0.06)	1.16	−0.26*** (0.06)	0.77	0.03 (0.05)	1.03	0.12* (0.05)	1.12	0.09 (0.05)	1.10	0.33*** (0.09)	1.38

Table 4 continued

	Private neglect		Public denigration		Public social disorder		Private conflict		Public violence		Prevalence of guns	
	Beta (Std. Error)	Odds Ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds ratio
Total Households (100 s)	0.01 (0.01)	1.02	0.07*** (0.01)	1.07	0.01 (0.01)	1.01	−0.01 (0.01)	0.99	−0.01 (0.01)	0.99	−0.07*** (0.02)	0.93
Nbhd type[e]												
Downtown	−0.97*** (0.22)	0.38	0.43 (0.22)	1.53	0.26 (0.19)	1.29	−0.09 (0.17)	0.92	−0.07 (0.18)	0.93	−0.57 (0.35)	0.57
Institutional	0.21 (0.13)	0.81	0.51** (0.15)	1.67	0.30* (0.12)	1.35	0.14 (0.11)	1.15	0.00 (0.11)	1.00	−0.32 (0.22)	0.73
Park	−0.11 (0.21)	0.90	−0.43 (0.24)	0.65	−0.36 (0.21)	0.70	0.11 (0.17)	1.12	−0.05 (0.18)	0.95	0.00 (0.33)	1.00
Street-Level Pseudo R^{2f}	.02***		.02***		.01***		.04***		.04***		.008***	
Tract-Level Pseudo R^{2f}	.003***		.004***		.001***		.01***		.007***		.001***	
N (roads/tracts)	123,265 (13,767/178)		123,265 (13,767/178)		123,265 (13,767/178)		123,265 (13,767/178)		123,265 (13,767/178)		123,265 (13,767/178)	

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 (Commercial Condo and Condo Parking)

[b] 100 s 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, with Residential acting as the reference group

[e] A series of dichotomous variables reflecting a tract's predominant usage, with Residential acting as the reference group

[f] Calculated using the equation recommended by Browne et al. (2005), where higher-order intra-class correlations (pseudo-R^2s) are calculated as $\left(\tau * E'(Y)^2\right)/\left(\left(\sum\tau + \sigma_u^2\right) * E'(Y)^2 + \sigma_e^2\right)$, where τ is the variance component for the higher-order units, $E'(Y)$ is the derivative of the expected value near the mean, Στ is the sum of all variance components for higher-order units, and σ_e^2 is the first-level (i.e., address-level) error variance

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

99% of variance was at the address level across outcomes. Consistent with the simpler analysis performed above, this provides more formal evidence that the concentration of crime and disorder at addresses is greater than what would be predicted by clustering at the street and neighborhood levels.

Persistence of Crime

Moving a step further, we sought to examine the importance of addresses, streets, and tracts in predicting persistence in crime and disorder between 2011 and 2012. This was done with multilevel models of the same form as the previous analysis, but with counts of reports in 2012 as the outcome. In addition, address-, street-, and tract-level residuals were extracted from the 2011 models, representing the extent to which a particular type of crime or disorder was greater or less than expected at each level while controlling for characteristics of the built environment. The residuals for each outcome measure were then incorporated as predictors in the corresponding model predicting 2012 outcomes. The strength of these cross-time parameters indicates the extent to which persistence operates at each level of analysis.

Across models all cross-time parameters were significant (p values <.001), but with very different magnitudes (see Table 5 for all parameters). The tract level featured the largest parameters (Bs = 0.94–1.25), indicating that an increase of one in the residual in 2011 was associated with a nearly equivalent increase in that form of crime or disorder in the following year. Parameters were somewhat smaller for streets (Bs = 0.36–0.83) and smallest for addresses (Bs = 0.04–0.11). Since each of these parameters was on the same scale, this would suggest that persistence is greater at the higher levels of spatial organization.

Additionally, we explored the role of interactions between the residuals at different levels in determining persistence. For example, the interaction between address and street residuals for private conflict asks, to what extent does the level of private conflict at the

Table 5 Parameter estimates from three-level models using address-, street-, and tract-level residuals from 2011 models predicting disorder and crime to predict the corresponding measure in 2012

	Private neglect	Public denigration	Public social disorder	Private conflict	Public violence	Prevalence of guns
Main effects only						
Address	0.04***	0.05***	0.08***	0.11***	0.11***	0.05***
Street	0.55***	0.36***	0.83***	0.83***	0.72***	0.28***
Tract	0.94***	0.95***	1.25***	1.11***	1.13***	1.03***
With interactions						
Address	0.04***	−0.03**	0.04***	0.12***	0.07***	−0.29**
Street	0.48***	0.31***	0.71***	0.77***	0.58***	0.25***
Tract	0.9***	0.96***	1.23***	1.01***	1.00***	1.11***
Address × street	0.05***	0.08***	0.11***	0.06***	0.11***	0.14***
Address × tract	0.07***	0.08***	0.08***	0.10***	0.14***	0.14***
Street × tract	−0.01	0.04	0.08	−0.01	0.15**	−0.00

n = 123,265 addresses nested in 13,767 street segments in 178 census tracts. Models also controlling for: addresses' land usage, number of parcels, and number of used parcels; street length, classification as main street, and predominant land usage; and census tract's total population, number of households, and type of use (see Table 4 for additional detail on usage types for all levels)

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

street level influence the persistence of private conflict at addresses on that street? Across all models, the interactions between address residuals and the residuals at the other two levels were positive and significant (address x street: Bs = 0.05–0.14, p values <.001; address x tract: Bs = 0.07–0.14, p values <.001). This suggests that persistence of a particular form of crime or disorder is greater at addresses that are in streets or tracts that also have an elevated level of that form of crime or disorder, and that the effect of the tract in these regards is slightly greater. Conversely, it appears that persistence at an address is less common or even unlikely on streets and in tracts that are not also characterized by elevated crime or disorder. In contrast, the interaction between street and tract was only significant for public violence (B = 0.15, $p < .01$).

Last, the reader will note that in two of the models (public denigration and prevalence of guns) the main effect of the address-level residual became negative with the inclusion of the interactions. This is a result of the main effect parameter being estimated at the mean level of the street- and tract-level residuals. Thus, when street- and tract-level residuals are higher, the effective address-level parameter is higher as well, becoming positive. For example, in the case of public denigration, if the street-level residual is 1, then the effective address-level parameter is 0.05 ($address\text{-}level\ parameter\ +.08{*}tract\text{-}level\ value = -0.03 + 0.08{*}1 = 0.05$).

The analysis of persistence was repeated for 2012–2013, producing nearly identical results (see Appendix for all parameters). Though a few parameters shrank or grew by non-trivial amounts, there was little in the way of qualitative differences. The one notable exception to this was the appearance of a positive, significant interaction between the street- and tract-level residuals for private conflict (B = 0.23, $p < .001$) and guns (B = 0.08, $p < .05$), though the latter just crested significance.

Persistence of Crime: A Closer Look

The results of the multilevel models with lags indicated that crime and disorder persist at addresses, but less strongly than at the street and tract levels. This sort of model only communicates the population-average effects, potentially obscuring any heterogeneity in the year-to-year trajectories that units of a particular geographic resolution might take. To examine this question more closely, we conducted a visual analysis, comparing the residuals from the 2011 and 2012 models (i.e., controlling for all covariates in Table 4) at each of the three geographic levels. Figure 1 illustrates the results for private conflict, which accounts for the greatest number of reports in these data and has also been shown in a recent study to be central to the year-to-year dynamics of a neighborhood (O'Brien et al., 2015).

The plots for tracts and streets (Fig. 1a, b) were as expected, each capturing a strong cross-time correlation, with high- and low-crime neighborhoods and hot- and coldspot streets remaining as such from year to year. For addresses, however, the story is strikingly different (Fig. 1c), suggesting three distinct types of addresses. First were those that had zero reports in both 2011 and 2012. Though this is the most numerous group (79%), they are not prominent in the graph because they are clustered near the origin. Second were those that generated reports in both years (5%), which create a relatively tight line in the middle of the graph, indicating that for those properties that generate reports yearly their level of crime and disorder is relatively stable. Third, there were properties that generated reports in one year and not the other (16%). Though these appear to be dispersed broadly across each axis, they did generate fewer reports in a single year than addresses that generated reports in both years (reports in 2012: $mean_{\text{reports in both years}} = 2.95$,

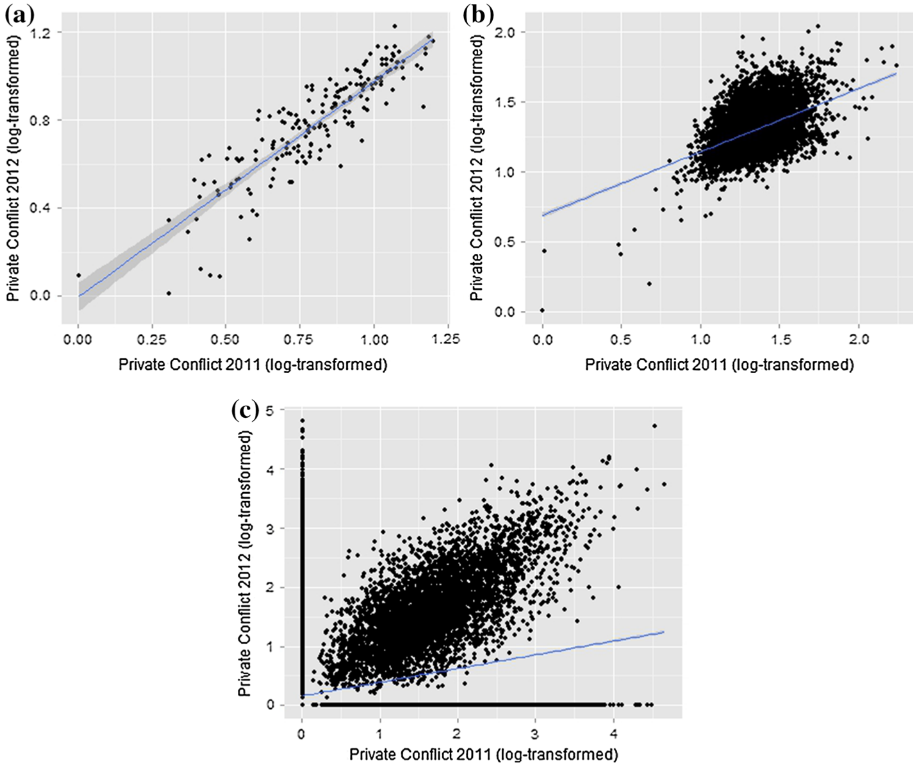

Fig. 1 Dot plots illustrating the correlation between levels of private conflict, controlling for covariates, for **a** tracts, **b** streets, and **c** addresses, with best-fit lines

$mean_{\text{reports in 2012 only}} = 1.48$; $t_{\text{df}=6628.3} = -15.15$, $p < .001$). Again, these analyses were replicated for 2012–2013, revealing the same relationships.

Discussion

The results here offer ample evidence that the law of concentration of crime extends to addresses, and in a manner that is over and above the concentrations that are known to exist for neighborhoods and streets. Across the six indices of crime and disorder, we found that addresses accounted for 95–99% of the variation in requests for service, indicating that a handful of "problem properties" generate an inordinate amount of the city's crime and disorder. Just as research on hotspot streets has demonstrated that there can be "bad" streets in low-crime neighborhoods and many safe streets in high-crime neighborhoods, our findings similarly suggest that problem properties can stand out on otherwise safe streets (i.e., properties with large positive residuals in the models when accounting for street and tract means) and that there are many addresses that generate no crime or disorder on hotspot streets (i.e., variance at the property level even when streets have a high overall level of crime and disorder). This builds on previous research, much of it examining repeat victimization, that has demonstrated the concentration of personal and property crimes and shootings at individual addresses (Sherman et al. 1989; Pierce et al. 1988; Farrell and Pease

2001; Kleemans 2001; Pease 1998; Bowers and Johnson 2005; Johnson et al. 2007; Wells et al. 2012; Youstin et al. 2011), expanding those findings to a broader set of types of disorder and crime.

The analysis of persistence, however, revealed a more nuanced set of patterns. On average, the level of crime and disorder at an address was predictive of a similar level in the following year, an effect that was present from 2011 to 2012 and from 2012 to 2013. Although many problem properties and no-crime properties were consistent from year to year, a notable number of properties exhibited crime in one year and not the other. This suggests the potential for “flare-ups” that last for a single year, or a portion thereof. It might also indicate that particular events can quickly stimulate or extinguish criminogenic dynamics at this highly localized level, a possibility we return to below.

Taken together, these two sets of findings endorse the value added by the address-level analysis, but do not obviate the relevance of hotspot streets and high-crime neighborhoods. First, the multilevel models found significant clustering at these two higher-order geographic levels for all indices of crime and disorder. This effect was stronger for streets than neighborhoods, but was relatively modest for both in comparison to the amount of variance attributable to addresses. Second, streets and neighborhoods exhibited a greater level of persistence than addresses from year to year. Judging by the visual analysis reported in Fig. 1, these relationships were consistent throughout the sample and were not weakened by unexpected “flare-ups.” Third, the interaction effects in the final set of models suggest that crime and disorder at the street or tract level might amplify address-level persistence, echoing previous findings that repeat victimization is more statistically prominent in high-crime areas (Trickett et al. 1995; Bennett 1995; Johnson et al. 1997). That is to say, problem properties on hotspot streets or in high-crime neighborhoods were more likely to be problem properties in the following year, and those on streets or in neighborhoods with low levels of crime were less likely to persist.

These findings shed additional light on the study of distribution of crime across the city, and the relative importance of micro-places and broader regions, offering insights for both theory and practice. Before exploring these implications, however, we would like to note a few limitations of the current study. Most apparent, the analysis here has been of a single city. It will be necessary to replicate these analyses in other cities of different sizes, forms, and cultures. Second, the study has leveraged as much longitudinal data as was available, but a three-year window is considerably smaller than those featured in some of the recent longitudinal work on street segments (e.g., Curman et al. 2015; Braga et al. 2010; Weisburd et al. 2012). A more telling examination of persistence would require such a database. Third, we have used requests for service here, which have some advantages—most importantly, geographic precision and the elimination of bias from police discretion—but also suffer from false positives (i.e., requests in the absence of an actual crime) and false negatives (i.e., failures to call when crime or disorder occurs) arising from the ability and willingness of constituents to accurately report crime and disorder. Further, there is evidence that such errors vary systematically across neighborhood (Klinger and Bridges 1997) and can lead to the underestimation of repeat events (Frank et al. 2012). While such weaknesses could create similar false positives and negatives in the identification of specific problem properties or hotspots, there may be fewer concerns for analyses of concentration and persistence, like the one presented here. This is illustrated by Hibdon et al.’s (2016) study of drug activity in Seattle, WA, reported elsewhere in this issue, which found that two different service request systems described the same pattern of concentration of drug activity, but identified different hotspots. That all said, a comprehensive study of problem properties will need to utilize measures of crime from multiple sources.

Implications for Theory and Practice

As evidence of localized concentrations of crime and disorder continues to accumulate, the criminology of place is increasingly faced with a fundamental question: which geographic unit or units should command our attention? The answer to this question would help theorists to determine the spatial resolution of the behavioral and social processes that are responsible for crime, and would offer guidance for policymakers and practitioners strategizing how to best allocate resources to manage public safety. The multilevel approach utilized here was a valuable contribution to this discussion as it permitted a direct comparison of the concentration of crime and disorder, both cross-sectionally and longitudinally, for addresses, streets, and tracts. Put in simple terms, the lesson learned was that all three levels are informative, though finer geographic resolutions can offer more precision whereas larger ones are more stable. An additional lesson was that the three levels are not independent of each other, but interact in determining the persistence of crime across years.

For theorists, this suggests that social or behavioral processes exist at each level, and that certain processes at one level can amplify those operating at a lower level. Turning to theory on repeat victimization, we might think of this in terms of flag and boost factors (Johnson 2008). Because these terms are more specific to the dynamics of crimes with a victim and offender (i.e., some factors "flag" a victim as vulnerable), we instead use the less eloquent but more generalizable descriptors "risk heterogeneity" and "event dependence." In terms of the former, most theorizing within the criminology of place has focused on routine activities, or the daily patterns of occupancy and behavior, that might generate or permit crime and disorder (Weisburd et al. 2012; Smith et al. 2000; Sherman et al. 1989; Wilcox et al. 2003). More recently, there has been a call for the incorporation of social disorganization theory (Weisburd 2015; Weisburd and Amram 2014; Weisburd 2012), which argues that the formal and informal relationships within a region manage behaviors and, in turn, regulate the level of crime and disorder (Shaw and McKay 1942/1969; Sampson 2012; Bursik and Grasmick 1993). In general, either of these theoretical frameworks could be applied to any of the three levels, though in practice routine activities are considered more relevant for micro-places, and social disorganization is more often the focus of neighborhood-level studies. This stands to reason as addresses and streets might have particular land uses that drive crime, whereas social dynamics may belong to a community that is coterminous with a broader geographic area.

The current study does provide some support for the dichotomy between the types of factors that create risk heterogeneity at different geographical levels. Land use had marked effects on the distribution of crime at the address and street levels, as did the designation of a street as a main street. Similar effects were less apparent for tracts. Put another way, though neighborhoods varied in their average level of crime and disorder, the distribution of crime within a neighborhood was determined largely by localized land usage. Future work should expand on this by incorporating measures of social disorganization, especially because there is evidence that some set of omitted and unmeasured variables is responsible for clustering at the tract level *and* that at least one of these variables amplifies persistence for addresses. It seems plausible that this could be owed to some aspect of social disorganization, as could the substantial unexplained variance at both the street and address levels. In addition to questions of risk heterogeneity, future work might also probe the role of event dependence (i.e., boost factors) in the long-term trajectories of crime at micro-places. Though we have not done so here, other research designs might establish whether one criminal event at a location increases the likelihood of others in the future. Similarly, it is possible, per theory on near repeats, that increased crime or disorder at an address will increase the level of risk for other addresses on the same street (Townsley et al. 2003).

There is also a need for a theoretical understanding of why addresses might switch between generating problems and generating none from one year to the next, and why the same is apparently not true for streets or neighborhoods. It may be that an address, given its atomic nature—i.e., that is, in most cases, a discrete, indivisible unit—is susceptible to events that can dramatically alter its tendency to generate or attract crime. This could involve factors that reconfigure local social and behavioral dynamics, making it more or less vulnerable to crime and disorder; for example, the sale of a house to new owners or the closing of a problematic bar or liquor store. It is also possible that an initial criminal or disorder event instigates similar events in the future. In contrast, a broader ecology, like a street or neighborhood, comprises a larger population and its constituent properties and spaces are often owned and managed by multiple entities. As such, the social and behavioral dynamics that characterize them likely feature greater resilience, thereby stabilizing levels of crime and disorder across time even in the face of change. This might occur through diffusion in events from one address to its neighbors; especially when one address undergoes a change that causes it to cease generating crime and disorder, it is possible these activities will move to nearby locations.

In terms of policy and practice, the potential opportunities of targeting problem properties come in two forms—prediction and enforcement—though there are remaining questions for each. In terms of the first, as the technology for collecting and managing digital administrative data has become increasingly available and sophisticated, many police departments across the country have been developing and implementing programs of *predictive analytics* that seek to identify where crime will occur in the future, rather than just interpret where it occurred in the past (Maciejewski et al. 2011; Wang et al. 2013; Perry et al. 2013). As noted, efforts at the prediction of burglaries have already concentrated on repeat victimization (Johnson et al. 2008; Tseloni and Pease 2014), and the analysis of persistence here offers further insights on the value that addresses offer to such efforts across types of crime and disorder. Most immediately, the fact that addresses do, on average, tend to generate similar levels of crime and disorder across years means that prospective models might utilize them to more precisely estimate the geographic locations and frequency of future crimes. This is especially true when the role of higher order geographies as well as the potential for diffusion between addresses is taken into account (e.g., Mohler et al. 2011; Johnson and Bowers 2004). That said, such an approach would be greatly strengthened by models that go beyond population averages and attempt to predict when and where an address is likely to be above a certain threshold, or even to predict where a flare-up is likely to occur (or die down).

In terms of enforcement, we return to one of the inspirations for this study: do the data here lend support to problem properties-oriented policing strategies? The answer to this question is yes, but only in a preliminary sense. The findings do suggest the value of focusing resources on particular properties, but they do not yet articulate how this might best be implemented. Most previous efforts of this sort have focused on specific types of properties, like drug markets (Eck 1994) and "nuisance" hotels (Bichler et al. 2013), making it possible to tailor enforcement to the primary characteristics of those places. As Grove et al. (2012) point out in their systematic review of programs intended to lower repeat victimization, they most effective approaches are those that successfully alter the characteristics that put a target at risk in the first place. This would imply that problem properties policies should aim to shift the underlying social and behavioral dynamics that generate or attract crime and disorder. In order to do this, we will first need greater understanding of the processes that are responsible for the concentration of crime at particular addresses, which would determine the specific activities that constitute a problem properties-oriented policy. This includes not only why crime persists at certain locations, but also why properties become problematic for short periods of time.

As the policies become more refined, it will be necessary to formally evaluate how effective they are. Importantly, much of this will need to focus on the role of addresses, streets, and tracts as units of enforcement. Empirically, an analysis of if and how events diffuse from one address to another will inform the extent to which a problem properties approach should focus exclusively on the address, or also on surrounding areas. Similarly, evaluation studies will need to establish whether targeting of problem properties in fact lowers crime and disorder, or simply displaces it to other locations on the street or in the neighborhood. That said, there is ample evidence to justify further experimentation with such policies, and these outstanding questions lay the groundwork for a research-policy agenda moving forward.

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Appendix

See Appendix Tables 6, 7 and 8.

Table 6 Distribution of reports of crime and disorder across addresses in 2012

	Mean	Max	# of Non-zeroes	Addresses generating 25% (%)	Addresses generating 50% (%)	Streets generating 50% (%)	Tracts generating 50% (%)
Private neglect	0.07	43	4983 (4.0%)	0.3	1.0	4.3	21
Public Denigration	0.09	85	7189 (5.8%)	0.5	1.6	4.2	18
Public Social Disorder	0.04	92	2996 (2.4%)	0.1	0.6	2.5	17
Private Conflict	0.21	36	13,930 (11.3%)	0.7	2.4	6.7	25
Public Violence	0.14	72	8444 (6.9%)	0.3	1.3	5.4	24
Prevalence of Guns	0.02	18	1668 (1.4%)	0.1	0.5	2.4	15

Table 7 Distribution of reports of crime and disorder across addresses in 2013

	Mean	Max	# of Non-zeroes	Addresses generating 25% (%)	Addresses generating 50% (%)	Streets generating 50% (%)	Tracts generating 50% (%)
Private neglect	0.07	37	4882 (4.0%)	0.3	0.9	4.5	21
Public denigration	0.08	60	6601 (5.4%)	0.5	1.5	4.6	20
Public social disorder	0.21	141	12,604 (10.2%)	0.1	0.6	2.6	20
Private conflict	0.32	404	18,437 (15%)	0.7	2.4	6.8	25
Public violence	0.19	99	9959 (8.1%)	0.3	1.4	5.3	24
Prevalence of guns	0.04	27	3039 (2.5%)	0.2	0.6	2.6	17

Table 8 Parameter estimates from three-level models using address-, street-, and tract-level residuals from 2012 models predicting disorder and crime to predict the corresponding measure in 2013

	Private neglect	Public denigration	Public social disorder	Private conflict	Public violence	Prevalence of guns
Address	0.04***	0.02**	0.05***	0.13***	0.09***	−0.16**
Street	0.58***	0.47***	0.71***	0.77***	0.65***	0.23***
Tract	1.11***	0.93***	0.92***	0.93***	0.93***	0.93***
Address × street	0.08***	0.1***	0.11***	0.08***	0.11***	0.10***
Address × tract	0.09***	0.11***	0.08***	0.12***	0.14***	0.08***
Street × tract	−0.02	0.04	0.19*	0.23***	0.22**	0.08*

$n = 123{,}265$ addresses nested in 13,767 street segments in 178 census tracts. Models also controlling for: addresses' land usage, number of parcels, and number of used parcels; street length, classification as main street, and predominant land usage; and census tract's total population, number of households, and type of use (see Table 4 for additional detail on usage types for all levels)

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

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