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Whence the Action? the Persistence and Aggravation of Violent Crime at Addresses, Streets, and Neighborhoods

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Abstract

Objectives: Researchers have long studied the persistence of violence and aggravation from disorder to violence in communities. Recently this work has begun to consider how these phenomena might operate simultaneously at multiple geographic scales. We examine the role of neighborhoods, streets, and addresses in these phenomena, presenting and assessing a five-part typology for cross-scale interactions. *Methods:* We calculated six measures of physical disorder, social disorder, and violent crime from administrative records for all parcels (i.e., addresses) in Boston, MA, for 2011–2016. Multilevel models used these measures to predict public violence and gun-related events in the following year at all three geographical scales and with cross-scale interactions. *Results:* Persistence was common at all scales. Aggravation from disorder to crime was greatest for

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addresses. Nearly all significant cross-level interactions involved addresses. The most common interactions were *reinforced persistence*, when persistence of violence at an address was reinforced by violence in the street or neighborhood; and *mediated persistence*, when persistence at a higher geographic scale operated through addresses with disorder. *Conclusions:* The study suggests that action is greatest at addresses, but streets and neighborhoods offer critical context. It also provides a framework for future work assessing the complementarity of communities and places.

Keywords
hotspots, communities and Crime, broken windows, urban crime, quantitative research < Research Methods

Introduction

Criminologists studying communities have long concerned themselves with the geographic *persistence* of crime and the *aggravation* of low-level issues, like physical and social disorder, to more serious problems, like violence. Historically, studies on these subjects focused on neighborhoods; high crime neighborhoods would continue to experience high crime (e.g., Sampson, 2012), and neighborhoods with disorder were vulnerable to increases in serious crime (Wilson & Kelling, 1982). Since the 1990s, however, the emergence of a criminology of place, which focuses on the dynamics of streets and addresses (Weisburd, Groff, & Yang, 2012), has complicated this picture. This is a trend that has rapidly accelerated in recent years, with studies examining the persistence of crime (e.g., Braga, Hureau, & Papachristos, 2011; e.g., O'Brien & Winship, 2017) and pathways from disorder to crime (Wheeler, 2017) at these more localized scales. Our understanding of how these multiple geographical scales drive these processes, however, remains inchoate, because few if any studies have examined addresses, streets, and neighborhoods simultaneously. Consequently, although there is much discussion of how each geographical scale "matters" for understanding crime (e.g., Sampson, 2012; Weisburd et al., 2016), there is little examination of how they work in concert to effect outcomes.

The current study examines the complementary roles of addresses, streets, and neighborhoods in driving persistence and aggravation of crime, defined respectively as the continuation of crime and the increased severity of crime over time at a given location. Using a longitudinal database of records generated by 311 and 911 systems in Boston, MA, we test how multiple forms of physical disorder, social disorder, and violent crime predict year-on-year change in violent crime. A series of multilevel models enables us to test two overarching research questions that comprehensively capture the complementarity between the three geographical scales. (1) Which independent effects of persistence and aggravation are relevant at each scale? For instance, is the presence of a certain type of disorder predictive of violent crime for a whole neighborhood, or only for the streets or addresses where it is located? (2) What are the cross-scale interactions between these effects? For example, is disorder at an address more likely to evolve into violent crime if disorder or crime is prevalent on the street or in the surrounding neighborhood? These cross-scale interactions have not been tested to date and have the potential to be diverse in nature. For this reason, we also develop and present a framework for studying and describing them.

In sum, the study makes not one but two contributions to the study of crime in communities. First, it describes the interdependent effects that addresses, streets, and neighborhoods have in the persistence and aggravation of crime, thereby advancing and synthesizing multiple nascent lines of inquiry. Second, it presents a novel framework for studying and describing cross-scale interactions in driving patterns of crime and disorder. Though applied here to the specific test case of persistence and aggravation, this framework is generalizable to other criminogenic processes that might operate at multiple geographical scales of interest. Before proceeding to the data and analysis, the following sections describe current evidence for persistence and aggravation at the multiple geographical scales; and lay out the framework for the cross-scale interactions we might expect to see.

Persistence and Aggravation of Crime at Different Geographical Scales

Research on the persistence and aggravation of crime and disorder have long, intertwined histories as they are two of the more fundamental ways of understanding the distribution of crime across time and space. Much of this work has been oriented around neighborhoods, specifically considering how community-wide rates of crime and disorder lead to future levels of crime (Bursik & Grasmick, 1993; Sampson, 2012; Sampson, Raudenbush, & Earls, 1997; Shaw & McKay, 1942/1969; Wilson, 1987). More recently, proponents of a criminology of place have highlighted the extent to which streets and addresses within neighborhoods play an independent role in shaping the distribution of crime and disorder across space (see Eck & Weisburd, 1995; Lee, Eck, O, & Martinez, 2017; Weisburd, 2015; Weisburd et al., 2016). In debunking the assumption that each neighborhood is a homogenous region in which all places experience the same conditions and dynamics, it has also highlighted the need to consider how criminogenic processes might operate at multiple scales.

Persistence and aggravation lend themselves well to a new multiscale perspective that integrates communities and places. For the former, there is good reason to believe that crime might persist at any and all of these scales. To wit, if individuals tend to persist in their offending over time (Le Blanc & Loeber, 1998), and the same is true for neighborhoods, why not each geographic scale in between? Meanwhile, theories of aggravation, the most famous being broken windows theory (BWT; Wilson and Kelling 1982), imply a neighborhood focus but are often agnostic to geographic scale as written. This leaves open the possibility that the mechanisms by which disorder leads to crime might be more pertinent at some geographic scales than others or that these mechanisms interact across geographic scales. Empirical research on persistence and aggravation has followed these opportunities, gradually extending from communities to places in recent years. As we summarize in the remainder of this section, the initial evidence from this work is informative, though it has not yet fully articulated the interplay of addresses, streets, and neighborhoods in these processes.

Persistence of crime at addresses, streets, and neighborhoods. Persistence of crime in communities is one of the oldest observations in urban criminology (Sampson, 2012; Shaw & McKay, 1942/1969). This is especially true when local demographics and other ecological features are consistent, meaning that the social dynamics underlying crime are themselves relatively stable (Bursik & Grasmick, 1993; Bursik, 1986). It has become increasingly apparent that a similar logic holds true for multiple scales of geography. First, research on repeat victimization has long noted that specific addresses that have experienced a crime are more likely to experience more crimes in the future (e.g., Farrell & Pease, 2001; Johnson et al., 2007; Trickett, Osborn, Seymour, & Pease, 1992). This relationship is especially strong in high-crime neighborhoods (Bennett, 1995; Johnson, Bowers, & Hirschfield, 1997; Trickett, Osborn, & Ellingworth, 1995), meaning that the context amplifies the addresses' persistent vulnerability (but also see Curtis-Ham, Evans, Burns, & Chainey, 2018 for counterevidence). Likewise, O'Brien & Winship (2017) used multilevel models to demonstrate that disorder and crime tended to persist across years at addresses, streets, and neighborhoods, independent of persistence at each of the other levels. As with the previous studies, addresses were more likely to experience persistence when the containing street or neighborhood also had higher levels of the same type of disorder or crime. What has not been tested to date is whether the persistence of one type of crime or disorder might interact with other types of crime and disorder; for instance, might persistence of violent crime at an address be influenced by the level of disorder in the neighborhood? As we will explore further below, there are multiple ways such interactions might manifest or interplay with other processes.

Aggravation of crime at addresses, streets, and neighborhoods. There are two main classes of theory for aggravation from crime to disorder. The first posits that elements of physical and social disorder in public spaces encourage crime. The most famous of these is *broken windows theory* (BWT; Wilson and Kelling 1982), which argues that disorder signals to would-be transgressors that criminal behavior will go unchecked in this space. This in turn can lead to more frequent and more serious crimes, or what Skogan (1990) has referred to as "the cycle of disorder and decline." An allied theory has concentrated on the way that certain types of disorder create *ecological advantages* that enable crime (e.g., abandoned houses can be used to hide contraband; Branas et al., 2016; St. Jean, 2007). A second perspective is that disorder does not so much invite crime as it acts as a precursor for it, as in O'Brien & Sampson's (2015) *social escalation theory* (SET). This perspective emphasizes that most violent events are not the result of random, predatory encounters but are between people who know each other and often have pre-existing tensions. As such, private disorder—like domestic conflicts and other disagreements between people sharing space—has the potential to escalate into more serious confrontations and to bubble out into public spaces.

Neither of the two perspectives on how disorder might evolve into crime stipulates which geographical scale would be most relevant. Though both have most often been described and examined at a neighborhood level, there is initial evidence that they might be relevant for understanding crime at places, as well. Of all theories regarding disorder and crime, BWT is the most studied to date, and the results have generated doubts about its relevance at the neighborhood level. Early critiques suggested that social dynamics were responsible for both disorder and crime, with disorder itself having no causal effect on crime (Sampson & Raudenbush, 1999). More recently, a meta-analysis found that the effectiveness of broken windows policing efforts in communities have been mixed at best and potentially unrelated to the elimination of disorder (Weisburd, Hinkle, Braga, & Wooditch, 2015). Meanwhile, another meta-analysis found no evidence that neighborhood disorder encourages violent or criminal behavior (O'Brien, Farrell, & Welsh, 2018).

There remains the possibility that public disorder might lead to crime at more localized scales. Numerous experimental studies revealing behavioral responses to disorder have used very narrow spatial and temporal windows, giving credence to the possibility that a person must be in the presence of disorder to be inclined to commit crime (Cialdini, Reno, & Kallgren, 1990; Keizer, Lindenberg, & Steg, 2008, 2013; Kotabe, Kardan, & Berman, 2016; O'Brien, Norton, Cohen, & Wilson, 2014; O'Brien & Wilson, 2011; Yang & Pao, 2015). Consistent with this, recent studies have found that disorder on a street segment predicts future crime there (Wheeler, 2017) and that its elimination leads to less crime (Braga & Bond, 2008). Meanwhile, the ecological advantages perspective on public disorder more explicitly indicates that abandoned buildings and the like enhance the opportunity for crime in the immediate vicinity, which have been borne out by associated studies (Branas et al., 2016; Furr-Holden et al., 2011; St. Jean, 2007). Taken altogether, these various pieces of evidence suggest that public disorder might be more likely to evolve into crime at places than throughout a community.

When considering which geographical scale should be most pertinent for private disorder to lead to crime, there is less evidence from which to start. O'Brien and Sampson's (2015) original study was conducted at the neighborhood level using a new methodology using administrative data to measure private disorder—otherwise difficult to observe—to test its role in driving violent crime. As such, there have been no other direct tests. Nonetheless, the theory draws on evidence of an interplay between household and community violence, either because they are perpetrated by the same individuals (Juarros-Basterretxea, Herrero, Fernandez-Suarez, Perez, & Rodriguez-Diaz, 2018; Kiss, Schraiber, Hossain, Watts, & Zimmerman, 2015) or feed into each other through interconnected stressors or social dynamics (Caughy et al., 2012; Cuartas, 2018). One might then argue that the escalations will be confined to individual households and their immediate surroundings. It is of course possible that, as the people engaged in these problematic relationships move about through daily activities, those same conflicts and escalations are liable to manifest in other places in the neighborhood. But it would appear that, just like public disorder, private disorder is more likely to lead to crime at discrete places than throughout the community.

A Taxonomy of Interactions Between Geographical Scales

A thorough multilevel examination of persistence and aggravation will necessarily test the direct, independent effects of public and private disorder on violent crime at each geographic scale. However, it is important to recognize that addresses, streets, and neighborhoods do not exist in isolation. Each is nested inside the next and thus the conditions at one level could influence dynamics at the locations therein (i.e., lower scales). This complementarity between scales has been highlighted by a handful of studies over the years, most often centered on how certain land uses—including parks and liquor stores—are more likely to generate issues when neighborhood-level factors raise the overall likelihood of crime (e.g., low income, high foot traffic; Boessen & Hipp, 2015; Deryol, Wilcox, Logan, & Wooldredge, 2016; Jones & Pridemore, 2019; Taylor, Haberman, & Groff, 2019). Similarly, as noted, persistence of crime at an address is reinforced by the presence of crime on the street or in the neighborhood. The analysis of aggravation from disorder to crime, however, greatly broadens the diversity of potential cross-scale interactions that might involve multiple types of crime and disorder. This creates a complexity whose study and interpretation currently lack guidelines, leading us to propose a taxonomy of cross-scale interactions. Though we develop this taxonomy for the purpose of the study at hand, it can also be extended to other theories of criminogenesis, including previous work on land use, which we return to in the Discussion.

Our taxonomy of cross-scale interactions is based in two considerations regarding the features at each geographical scale that are predictive of the outcome. (1) Is the predictor at the lower geographical scale the same as or different from the outcome? And (2) Are the predictors at the two geographical scales the same or different? This makes for a 2×2 matrix from which we derive a five-part taxonomy, with one of the quadrants split into two types. All of these interactions assume reinforcing effects of crime and disorder across scales, which would be observed as positive parameters in a model. We also take into account a sixth type of interaction in which the parameter is negative. As we discuss, we consider instances of this last category, at least in the context of persistence and aggravation of crime, to be statistical artifacts.

The five-part taxonomy (plus negative interactions) is as follows (also see Table 1):

(1) *Reinforced persistence* is the class of interaction tested in O'Brien & Winship (2017) and the repeat victimization literature (Bennett,

1995; Johnson et al., 1997; Trickett et al., 1995), where the presence of a single type of disorder or crime at a given scale is likely to continue from year to year, and that this is reinforced by the prevalence of the same type of disorder or crime at a higher geographic scale. For example, violent crime at an address is more likely to persist if the street or neighborhood also has high levels of violent crime.

(2) *Reinforced aggravation* is a parallel of reinforced persistence. Aggravation describes when one form of disorder or crime predicts another in the following year. Reinforced aggravation then occurs when that effect is amplified by the presence of the same type of disorder or crime at a higher geographical scale. While we anticipate that disorder is more likely to lead to violent crime at places, it would seem feasible that the widespread presence of disorder in a community could enhance these effects. Thus, we hypothesize that reinforced aggravation will be present, albeit less prevalent than reinforced persistence.

(3) *Moderated persistence* is similar to reinforced persistence in that the likelihood of a single type of disorder or crime at a place continuing across years depends on conditions at a higher geographic scale. In contrast, the persistence is moderated by a different type of disorder

Table 1. Taxonomy of Cross-Level Interactions for Persistence and Aggravation, Organized by Whether the Predictors at the two Geographical Scales and the Outcome Reference the Same Type of Event.

Lower-level Predictor = Outcome	**Yes**	**Reinforced Persistence** e.g., address violence * street violence → violence	**Reinforced Aggravation** e.g., address violence * street violence → guns
Higher-level Condition = Lower-level Predictor	**No**	**Moderated Persistence** e.g., address violence * street private conflict → violence	*Higher-level condition = outcome* **Mediated Persistence** e.g., address violence * street guns → guns *Higher-level condition ≠ outcome* **Moderated Aggravation** e.g., address violence * street private conflict → guns

or crime at a higher level. An example is if the persistence of violent crime at an address were more likely if the street or neighborhood had high levels of public social disorder. Given that the localized persistence would presumably be more directly related to future violent crime than a different condition at a higher level, we believe this will be a less common type of interaction.

The fourth quadrant comprises cases in which the lower-level predictor is different from the outcome and from the higher-order moderator, but it does not stipulate whether the higher-order moderator is the same as the outcome variable or not. For this reason we break it into two groups:

(4) *Mediated Persistence* occurs when the form of crime or disorder at the higher geographical scale is the same as the outcome. An example would be if the likelihood of private conflict at an address escalating into violence were moderated by the level of violence on the containing street or neighborhood. This is noteworthy because it would indicate that the persistence at the higher geographical scale is being mediated at least in part by its operation through aggravation at the lower level. Put another way, violence in the community persists through places that are vulnerable to such escalations. As this aligns with our understanding of aggravation at places being exacerbated or alleviated by community-level processes, we hypothesize that mediated persistence will be relatively common.

(5) *Moderated aggravation* is when the form of crime or disorder at the higher geographical scale is different from both the lower-order predictor and the outcome. An example would be if private conflict at an address predicted violence in the following year and this effect were moderated by the level of social disorder on the containing street or neighborhood. In a generalized sense, this class of interaction entails two different forms of crime and disorder interacting across geographic scales to influence the prevalence of a third form of crime or disorder. There is no clear theoretical reasoning for why this would be the case, for which reason we anticipate this will be the least common type of interaction.

Last, we take into the account the possibility of negative interactions between forms of crime and disorder at multiple geographical scales. Substantively, these would imply that disorder or crime at one level is *diminishing* the strength of persistence or aggravation at another level, for which there is little if any theoretical justification. More likely, such relationships are statistical artifacts. First, collinearity will be high with multiple measures of crime and disorder each with multiple interaction effects included in a single model, especially between each interaction effect and the main effects it comprises. Second, the logic of a regression is that all effects are additive, which might be untenable in practice. For instance, if multiple forms of crime and disorder that predict future violence are present at an address and its street and neighborhood, additive effects might overstate the overall likelihood of violence. In either of these circumstances, negative interactions could emerge as correction to imprecise predictions.

As hinted at throughout, we hypothesize that some of the five types of interactions will be more prevalent than others. On the one end of the spectrum, we already have evidence for reinforced persistence and thus anticipate that it will be one of if not the most frequent types of interaction. We then expect mediated persistence and reinforced aggravation to be relatively common because there is reason to believe that the higher order factor could potentially exacerbate a process already prone to generating violence at a given place. The same argument, however, is harder to make for moderated aggravation and moderated persistence, as the higher order factor is less proximate to both violence or the current vulnerability to aggravation. We thus hypothesize they will be uncommon if present at all. Last, we note that we are not just measuring "places" and "communities," but have three levels of analysis: addresses, streets, and neighborhoods. Among the three, we anticipate that addresses will operate most like "places" as conceptualized, with the greatest relevance of disorder and the most likelihood of experiencing interactions with the other geographical scales; that neighborhoods will be most like "communities;" and that streets will fall somewhere in between.

Current Study

The current study tests the relative strength of persistence and aggravation at addresses, streets, and census tracts (approximating neighborhoods), including an examination of how these processes interact across geographical scales. To do so, it leverages a six-year archive of records from the 311 and 911 systems in Boston, MA (2011–2016), which receive and compile requests for non-emergency (e.g., graffiti removal) and emergency (e.g., shooting) government services, respectively. Previous work with these data has developed groupings of case types that reflect particular dimensions of crime and disorder: two for physical disorder in private and public spaces; two for social disorder in private and public spaces; and two for violent crime with and without guns, respectively (O'Brien & Sampson, 2015; O'Brien, Sampson, & Winship, 2015). The measures of public disorder are those that would be most consistent with BWT and related theories, like ecological advantages. The measures of private disorder are most relevant for testing SET. In addition, although not an explicitly theorized form of aggravation, possibly because it is a rather obvious one, the analytic strategy will also examine the interplay between public violence and gun-related events over time.

The records are coordinated with other data sets using the Geographical Infrastructure for the City of Boston (O'Brien et al., 2019), a multilevel database that organizes the geography of the city at 17 geographic scales. It includes basic descriptors of urban form while also providing the capacity for nesting levels within each other (e.g., street segments within tracts), enabling the analysis that follows. We leverage this nested structure with multilevel models, in this case four-level models with addresses nested within streets nested within neighborhoods (i.e., census tracts) nested within years (see Methods for more detail; Raudenbush & Bryk, 2002). These models then use levels of violence and disorder from the previous year, along with time-invariant characteristics (e.g., land use), to predict events in the focal year. We elaborate further on this estimation strategy in the next section.

We limit our analysis to census tracts that are primarily residential, excluding those that are in downtown areas or dominated by parks or institutions (e.g., universities), as these other contexts have distinct land use patterns that create considerable variations in levels of crime and disorder (e.g., downtown areas have much higher rates of public social disorder, physical disorder, and violence) and their correlates (e.g., the correlation between median income and crime is strongly negative in residential tracts but negligible in others). Thus, an analysis of all census tracts would capture heterogeneous relationships, confounding parameter estimates and their interpretation. Importantly, "primarily residential" does not indicate a lack of land use diversity. Such neighborhoods include business districts, parks, and other amenities designed to serve local residents, thereby ensuring the relevance of the results to other studies focused on these non-residential land uses. We also exclude addresses that have undergone substantial alterations in their land use during the study period as these exogenous shocks might complicate patterns of persistence and aggravation in unmeasurable ways.

Methods

Data Sources

The study utilizes archives of requests for service received by the City of Boston's 311 system and dispatches made by the 911 system. For the 911 system, we use records from 2011–2016; because the 311 system provides only predictor variables (see below), these records are only necessary for 2011–2015. Records from the 311 system include requests received by hotline as well as associated web platforms (e.g., smart phone application).

Over the period analyzed, the City received 904,105 unique requests through the 311 system[1] and made 4,031,816 unique 911 dispatches. Of these, 843,664 311 requests and 3,680,762 911 dispatches referenced an address or intersection that could be uniquely identified in the list of known locations maintained by the City of Boston (see section on Unit of Analysis; effective geocoding rates of 93% and 91%, respectively).[2] Data were further limited to those events attributed to an address (i.e., excluding intersections because there is no way to systematically attribute such cases to an address or to analyze intersections as equivalent to addresses by imputing the variables used to describe the latter; 657,634 311 reports and 3,572,858 911 dispatches). These locations indicated where services were required and thus where the event or issue had occurred. Both systems utilize 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.

Units of Analysis

The fundamental unit of analysis for the study is the land parcel, or lot that contains one or more properties (e.g., condominiums in a building), because 311 and 911 requests do not reliably specify individual properties within parcels. Parcels are the formal unit most similar to the colloquial "address." The Boston Area Research Initiative's Geographical Infrastructure for Boston (GI; O'Brien et al., 2019) maps all parcels identified by the City of Boston's Tax Assessor 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 geographies.[3]

The proceeding analysis is limited to census tracts that are predominantly residential, excluding those that are in the downtown district, dominated by institutions (e.g., universities), and parks, as these have distinct levels and correlates of crime and disorder that would confound the analysis and complicate interpretation. Given the longitudinal analysis, we used tax assessments to identify and exclude any parcels that underwent a change in land use or substantial change in valuation,[4] each of which indicate an exogenous shock that might interrupt patterns of persistence and aggravation in unmeasurable ways. We report a series of sensitivity analyses in the Supplementary

Online Materials (SOM) demonstrating these differences for all exclusion criteria. We also excluded parcels for which there was no available count of the number of properties therein, as these are meaningful land use characteristics (2.9% of parcels; see Measures).[5] This resulted in a final, three-level database of 70,224 land parcels situated on 9,153 street segments within 121 census tracts.[6]

Measures

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.[7] 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., the maintenance of 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 & 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., landlord-tenant conflicts). The indices of violent crime were: *public violence* that did not involve a gun (e.g., fight); and *gun-related events*, as indicated by shootings or other incidents involving guns. SOM contain constituent case types for each index and their frequencies for 2011.

Counts of each of the six measures of disorder and crime were tabulated for each parcel in each year. To test the effects of events at parcels, streets, and tracts, we needed to create independent measures at each level for each year. To accomplish this, we ran a series of cross-sectional three-level models controlling for land use and number of units at the parcel level; segment length, number of properties, predominant land use, and whether it is a main road or dead end at the street level; and population size at the tract level (all descriptive statistics available in SOM; also see O'Brien et al., 2019). We then extracted the Bayesian residuals from these models at all three levels. Each of these Bayesian residuals is a measure of the extent to which that form of crime or disorder was more prevalent than expected given land use characteristics, independent of the other two geographic scales. We then use these as the independent variables predicting violent crime and guns in the next year, except in the case of parcels for which we use a binary measure of whether there were any events of that type in the previous year (owing to the low number of events across parcels; e.g., 6.1% of parcels had a violent event in 2011).

Analysis

We ran two sets of multilevel models predicting violent crime and guns at each parcel in each year 2012–2016 (because there were no lagged measures available for 2011), with parcels nested in streets, streets nested in census tracts, and census tracts nested in years. The reader might note that such models are typically designed with years (or time points) as the lowest level of analysis. Formally, this makes the lowest level of analysis parcel-years. The next three levels, in this case parcels, streets, and neighborhoods, then have time-invariant attributes that are applied to all parcel-years therein. This, however, makes it impossible to accommodate predictors for streets and neighborhoods that vary by year. This includes our variables quantifying violence and disorder in the previous year for streets and neighborhoods, which are central to our research questions. Nonetheless, the establishment of years as the highest order of analysis yields interpretations that are consistent with our research questions; for example, the impact of a parcel's disorder in the previous year on future violence is modeled on the same parcel's level of disorder relative to other parcels on that street, its street's violence relative to other streets in that tract, and its tract's violence relative to other tracts in the previous year, all relative to the average citywide patterns for the focal year. The models were run using the lme4 package in R (Bates, Machler, Bolker, & Walker, 2015).

We ran two sets of models, each of which included two models apiece for violence and gun-related events, the first predicting whether a parcel had any events of the given type, and the second predicting the count of such events at parcels with at least one; this is effectively a hurdle model design (both types of models used logit links, accounting for the dichotomous and Poisson distributions of the outcome variables, respectively). The first set of models included only main effects at each geographical scale, taking the form:

$$\eta_{jklt} = \psi_{0klt} + \psi_{1klt} * x_{1jklt} + \ldots + \psi_{nklt} * x_{njklt} + \varepsilon_{jklt} \tag{1}$$

$$\psi_{0klt} = \pi_{00lt} + \pi_{01lt} * x_{(01)klt} + \ldots + \pi_{0nlt} * x_{(0n)klt} + \epsilon_{0klt} \tag{2}$$

$$\pi_{00lt} = \beta_{000t} + \beta_{001} * x_{(001)lt} + \ldots + \beta_{00n} * x_{(00n)lt} + r_{00lt} \tag{3}$$

$$\beta_{00t} = \gamma_{0000} + \mu_{000t} \tag{4}$$

where η_{jklt}, was the outcome variable (i.e., presence or absence of a report or frequency of reports generated) at the *j*th parcel on the *k*th street in the *l*th census tract in the *t*th year; and ψ, π, β, and γ are parameter estimates for predictors at the parcel, street, tract, and year levels, respectively, noting that the year-level equation is intercepts only; and ϵ_{jklt}, ϵ_{0klt}, r_{00lt} and μ_{000t} are the error terms at each level. The parcel, street, and tract equations all included lagged measures of disorder or crime in the previous year. At the parcel level these were binary measures of whether a parcel had an instance of a given type of issue in the previous year. At the street and tract levels they were Bayesian residuals for the frequency of that type of disorder or crime above expected given land use and other structural characteristics. Because these latter measures were Bayesian residuals from cross-sectional multilevel models, they were already centered before being entered into the model. The models also included the same control measures regarding land use and infrastructure included in the three-level models used to create annual measures of disorder and crime above expected (see section on Measures), plus ethnic composition (proportion Black, Hispanic, and Asian, all log-transformed) and median income for census tracts. Many of these were dichotomous variables and thus were not centered. The nested nature of multilevel models accounts for spatial diffusion between parcels on the same street and streets in the same tract, but to account for additional diffusion between tracts, we included a spatiotemporal lag predictor for the outcome variable (i.e., public violence or prevalence of guns, respectively). For each census tract, the lag was measured as the average value of the outcome variable in adjacent census tracts in the previous year. For final specification of the models, the lagged crime and disorder measures at each level were then trimmed to exclude nonsignificant effects. This was necessary given extensive collinearity between predictors (e.g., 10 of 15 correlations between tract-level measures had $r = 0.5$ -.85) and improved the fit of models (all saw a drop in Akaike Information Criterion (AIC), 3 of 4 had $\Delta > 4$, a standard cutoff for improved fit).

The second set of models introduced cross-level interactions for each of the significant predictors present at the conclusion of the first set of models. This method is consistent with the marginality principle, which argues that when selecting interaction effects from a large set of predictor variables, it is unparsimonious to consider interactions between variables that do not already demonstrate main effects (Nelder, 1998). The models took the form:[8]

$$\eta_{jklt} = \psi_{0klt} + \psi_{1klt} * x_{1jklt} + \cdots + \psi_{nklt} * x_{njklt} + \varepsilon_{jklt} + \qquad (5)$$

$$\psi_{11lt} * (x_{1jklt}\, x_{(01)klt}) + \ldots + \psi_{nnl} * (x_{njklt}\, x_{(0n)klt}) + \quad (6)$$

$$\psi_{1k1} * (x_{1jklt}\, x_{(001)lt}) + \ldots + \psi_{nkn} * (x_{njklt}\, x_{(00n)klt}) + \quad (7)$$

$$\pi_{j11} * (x_{(01)klt}\, x_{(001)lt}) + \ldots + \pi_{jnn} * (x_{(0n)klt}\, x_{(00n)klt}) \quad (8)$$

$$\psi_{0klt} = \pi_{00lt} + \pi_{01lt} * x_{(01)klt} + \ldots + \pi_{0nlt} * x_{(0n)klt} + \epsilon_{0klt} \quad (9)$$

$$\pi_{00lt} = \beta_{000t} + \beta_{001} * x_{(001)lt} + \ldots + \beta_{00n} * x_{(00n)lt} + r_{00lt} \quad (10)$$

$$\beta_{00t} = \gamma_{0000} + \mu_{000t} \quad (11)$$

All interaction effects were introduced at once and then trimmed stepwise to remove nonsignificant predictors. This was done to avoid artifacts of collinearity (correlations between interactions and parcel-level measures had *r*s = .44 -.80) and eliminate noise. The trimmed models showed better fit than the saturated models (Δs in AIC = 49, −5, 37, 17). Given the large number of parameters tested, we established significance based on *q*-values for multiple comparisons (Storey, Bass, Dabney, & Robinson, 2019).

Results

Descriptive Statistics

As other studies have noted, incidents of violent crime events were relatively infrequent across parcels (O'Brien & Winship, 2017; Pierce, Spaar, & Briggs, 1988; Sherman, Gartin, & Buerger, 1989). 6.1% of parcels had at least one instance of public violence in 2011 and 1.3% had at least one gun-related event (see Table 2 for distribution of all six types of crime and disorder across parcels, streets, and neighborhoods). Given the higher prevalence of incidents of public violence, we use it as the primary illustration of descriptive relationships relevant to persistence and aggravation of crime.

There was substantial consistency in which parcels experienced public violence across years. For example, 35.7% of the parcels with a violent event in 2011 experienced one or more in 2012. This rate was modestly higher for parcels in census tracts with above average levels of violence (38.7%), providing preliminary evidence for both persistence and reinforced persistence.

Parcels saw some shifts in the types of crime and disorder occurring there, supporting the argument for aggravation. For instance, 24.3% of

Table 2. Distribution of Reports of Physical Disorder, Social Disorder, and Violent Crime Annually Across Parcels (i.e., Addresses), Streets, and Tracts in Boston's Residential Neighborhoods.

	Parcels		Streets		Tracts	
	Mean (% >0)	Range	Mean (% >0)	Range	Mean (sd)	Range
Public Social Disorder	0.03 (2.0%)	0–51	0.29 (16.8%)	0–71	17.75 (13.93)	0–108
Private Conflict	.07 (5.0%)	0–20	0.90 (40.6%)	0–20	47.24 (29.50)	3–137
Violence	0.14 (7.0%)	0–99	1.54 (44.4%)	0–110	88.96 (61.15)	3–300
Gun-Related Events	0.02 (1.7%)	0–17	0.27 (15.9%)	0–17	15.11 (15.28)	0–76
Private Neglect	0.09 (4.6%)	0–43	1.24 (37.1%)	0–43	61.74 (44.53)	2–227
Public Denigration	0.08 (4.8%)	0–85	0.99 (33.8%)	0–87	44.83 (35.47)	0–332
Sample Size	70,224		9,153		121	

Note: Measures based on all annual measures. 2011–2016 for social disorder and violent crime and 2011–2015 for physical disorder.

parcels experiencing either public social disorder or public denigration in 2011 had a violent event in 2012, which is elevated relative to 6% of all parcels. Likewise, 24.1% of parcels experiencing either private conflict or private neglect in 2011 had a violent event in 2012. These two proportions were somewhat higher for parcels in tracts with above average levels of violence (31.0% and 28.1%, respectively), again suggesting an interaction between a parcel and its broader context. Obviously, these findings are descriptive and require a more comprehensive evaluation through the regression models to follow.

Aggravation and Persistence at Three Geographic Scales

Our first set of multilevel models used all six forms of disorder and crime in one year to predict the incidence of public violence and gun-related events in the following year, nesting parcels within streets within tracts within years. For each of the two outcomes, there were two models, one predicting the likelihood of any such events, the second predicting the number of events at parcels with one or more occurrence. The models used only direct effects. Note that odds ratios at the parcel level reflect the difference in likelihood of any violent or gun events (binary model) or an additional event (count model) between parcels with and without one or more events of the predictor type of crime or disorder in the previous year; at the street and tract levels it reflects the same likelihoods given an increase of one standard deviation in the predictor type of disorder or crime. See Table 3 for all parameter estimates.

Persistence was universal across the models. The presence of public violence and gun-related events each predicted a greater likelihood and number of the same type of event in the following year for parcels, streets, and tracts (all 12 p-values <.001, except for one p-value <.01). Aggravation was most frequent at the parcel level, where the presence of all other forms of disorder and crime predicted a greater likelihood of a violent event and a gun-related event in the next year (all 10 p-values <.001). All measures except for public denigration predicted more violent events; public social disorder and private conflict both predicted more gun-related events (4 of 6 p-values <.001, other 2 p-values <.01).

There was less evidence of aggravation at the street and neighborhood levels. There was one effect at each level consistent with BWT (and related theories). Social disorder on the street was associated with a higher likelihood of violence in the following year (B = 0.03, p <.001; O.R. = 1.03), and public denigration in the census tract was predictive of a higher likelihood of a gun-related event (B = 0.07, p <.01; O.R. = 1.07). There were four effects for streets and two for tracts consistent with SET. The prevalence of private conflict and private neglect each predicted a greater likelihood of public violence on a street (both parameters B = 0.04, p <.001; O.R. = 1.04) and a tract (private conflict: B = 0.08, p <.001; O.R. = 1.08; private neglect: B = 0.05, p <.01; O.R. = 1.05). Private conflict was also predictive of the likelihood of gun-related events on a street in the following year (B = 0.07, p <.001; O.R. = 1.08), and private neglect was predictive of a greater number of gun-related events on a street (B = 0.03, p <.05; O.R. = 1.03).

A number of other significant parameters reflected interplay between public violence and gun-related events. Though these are not pertinent to the theories of aggravation presented above, they and any associated interactions in the next stage of the analysis have the potential to be relevant to the broader story of how crime persists and evolves at different geographic scales. As already noted, public violence and gun-related events were each predictive of the other in all models at the parcel level, except violence was not predictive of the frequency of gun events. Additionally, they were each predictive of the likelihood (but not the frequency) of the other at the street and tract levels.

Interactions Across Geographic Scales

The second set of multilevel models tested cross-level interactions between each of the significant predictors present in the final main effect models, with

Table 3. Multilevel Models Predicting the Likelihood and Frequency of Violence and gun Events in the Following Year Based on Events at the Parcel (i.e., Address), Street, and Census Tract Levels.

	Violence (Binary)		Violence (Count, Non-Zero)		Guns (Binary)		Guns (Count, Non-Zero)	
	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio
Parcel Characteristics								
Social Disorder (Bin.)	0.84*** (0.04)	2.31	0.30*** (0.02)	1.36	0.68*** (0.05)	1.98	0.14*** (0.03)	1.15
Private Conflict (Bin.)	0.51*** (0.02)	1.67	0.15*** (0.01)	1.16	0.31*** (0.04)	1.36	0.09** (0.03)	1.09
Violence (Bin.)	1.10*** (0.02)	3.00	0.23*** (0.01)	1.25	0.81*** (0.04)	2.25		
Guns (Bin.)	0.67*** (0.04)	1.96	0.25*** (0.02)	1.29	0.89*** (0.05)	2.44	0.15*** (0.03)	1.16
Private Neglect (Bin.)	0.31*** (0.03)	1.36	0.05** (0.02)	1.05	0.20*** (0.04)	1.23		
Public Denigration (Bin.)	0.27*** (0.03)	1.31			0.20*** (0.05)	1.22		

(continued)

Table 3. (continued)

	Violence (Binary)		Violence (Count, Non-Zero)		Guns (Binary)		Guns (Count, Non-Zero)	
	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio
Street Characteristics								
Social Disorder	0.03*** (0.01)	1.03						
Private Conflict	0.04*** (0.01)	1.04			0.07*** (0.01)	1.08		
Violence	0.18*** (0.0^1)	1.20	0.14*** (0.005)	1.15	0.16*** (0.01)	1.17		
Guns	0.03*** (0.01)	1.03			0.09*** (0.01)	1.09	0.04*** (0.01)	1.04
Private Neglect	0.04*** (0.01)	1.04					0.03* (0.01)	1.03
Public Denigration								

(continued)

Table 3. (continued)

	Violence (Binary)		Violence (Count, Non-Zero)		Guns (Binary)		Guns (Count, Non-Zero)	
	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio
Tract Characteristics								
Social Disorder								
Private Conflict	0.08*** (0.02)	1.08						
Violence	0.13*** (0.02)	1.14	0.08*** (0.01)	1.09	0.10** (0.04)	1.10		
Guns	0.05* (0.02)	1.05			0.37*** (0.04)	1.44	0.09** (0.02)	1.09
Private Neglect	0.05** (0.02)	1.05						
Public Denigration					0.07** (0.02)	1.07		

(continued)

Table 3. (continued)

	Violence (Binary)		Violence (Count, Non-Zero)		Guns (Binary)		Guns (Count, Non-Zero)	
	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio	Beta (SE)	Odds Ratio
Observations	351,120		25,515		351,120		6,640	
Akaike Inf. Crit.	143,617		80,642		53,020		16,256	
Note:	*p < 0.05; **p < 0.01; ***p < 0.001							

Note: Observations are of 70,224 parcels (i.e., addresses) that did not experience substantial change in value on 9,153 street segments within Boston's 121 predominantly-residential census tracts over 5 years (see Methods for more detail). Measures of crime and disorder are lagged from the previous year. At the address level they are binary measures reflecting the presence (or not) of that type of crime or disorder. At the street and tract levels they are centered, continuous measures drawn from the Bayesian residuals for the given unit of measurement from multilevel models controlling for land use characteristics. Models also controlled for: land use, number of units, and owner-occupancy status at the address level; length, main street classification, dead end, number of units, average value per square foot, and street type (per predominant land usage) at the street level; and population density, percentage Black population, percentage Asian population, percentage Latinx population (all ethnicities log-transformed), median household income, proportion of families living in poverty, and measures of the outcome measure (i.e., violence or guns) in adjacent tracts in the previous year (i.e., spatial lag).

nonsignificant interactions trimmed stepwise (see Analysis for more). In the final models 32 of the 40 main effects identified in the original set of models remained significant positive predictors. In addition, there were 18 significant positive interaction effects and 15 negative ones. We summarize these interactions according to our five-part taxonomy of cross-level interaction effects and the theories of aggravation rather than walking through them one-by-one (see Table 4 for a summary and SOM for all parameter estimates). The interaction effects strengthened the predictive power of all four models (violence (binary): Δ AIC = 431; violence (count): Δ AIC = 711; guns (binary): Δ AIC = 71; guns (count): Δ AIC = 86).

Of the 18 positive interaction effects, 10 were between parcels and streets, 5 were between parcels and tracts, and 3 were between streets and tracts. The most common interaction type was reinforced persistence, with 4 of 8 possible effects involving parcels being significant. All 3 interactions between streets and tracts were of this type (of 4 possible). In such cases, public violence and gun-related events were persistent at a parcel, contingent in part on the prevalence of the same type of event at the street or tract level. To illustrate (also see Figure 1), violence at a parcel on a street with an average level of violence had an odds of 2.51 of persisting in the next year relative to appearing at a parcel on the same street with no previous violence. Moving to a street at the 75th percentile of violence, the odds ratio was 3.04 (or a relative odds of 1.21 to the parcel on the average street), and the odds of violence occurring at a new parcel was 1.11. As such, the impact of being on a street with above average violence was twice as important (1.21 vs. 1.11) for parcels with pre-existing violence than those without violence.[9]

The next most frequent type of interaction was mediated persistence, in which a different form of crime and disorder at a parcel predicted public violence or gun-related events the following year provided the street or tract was above average for violence or gun-related events, respectively. There were 7 such parameters. There were 5 cases of reinforced aggravation, wherein the relationship between a form of disorder or crime and either public violence or gun-related events was amplified by the presence of the same type of disorder. Examples of each of these are illustrated visually in Figure 1. There were no cases of moderated aggravation, wherein aggravation from one type of disorder or crime to public violence or gun-related events was moderated by the prevalence of a different form of disorder or crime at the street or neighborhood level; or moderated persistence, wherein violence or guns continued across years but moderated by a different type of disorder or crime at a higher level.

Table 4. Summary of Significant Main and Interaction Effects by Geographical Scale from the Four Expanded Models Using Interaction and Main Effects to Predict the Likelihood and Frequency of Violence and gun-Related Events.

Main Effects	Parcel	Street	Tract
Persistence	¾	3/4	2/4
Aggravation	14/20	6/20[a]	4/20
Interactions			
	Parcel x Street	**Parcel x Tract**	**Parcel x Tract**
Reinforced Persistence	2/4	2/4	3/4
Moderated Persistence	0/20	0/20	0/20
Mediated Persistence	4/20	2/20	0/20
Reinforced Aggravation	4/20	1/20	0/20
Moderated Aggravation	0/80	0/80	0/80
Negative	9/144	5/144	1/144

Note: Based on full parameter estimates reported in SOM. Parcels are the operationalization of addresses.
[a]– Guns at the street level became a negative predictor of gun-related events after introduction of interactions.

Only 7 of the 18 interaction effects were relevant to the two main theories of aggravation, and they were nearly evenly split between them. Four interaction effects involved public social disorder, making them relevant to BWT, though none involved public denigration. Three involved private conflict or private neglect, making them relevant to SET. Four of these 7 interactions were cases of mediated persistence, 3 involving public social disorder and 1 involving private conflict. Three were reinforced aggravation, one for each of the measures of disorder. In all seven interactions the measure of disorder was at the parcel level. It was only relevant at the street or tract level in the cases of reinforced aggravation.

There were also four interactions pertaining to the relationship between violence and guns, a seemingly two-way form of aggravation that we did not necessarily set out to test. Two of these were cases of mediated persistence and two of reinforced aggravation. Last, there were 15 negative interactions. As noted, these were expected as the result of collinearity and correction for additive effects. For instance, all 15 involved a measure of violence or gun-related events, which also typically had other positive significant main and interaction effects in the model and were typically smaller than the main effect at the higher geographical scale. This was consistent with the interpretation that these negative effects were effectively placing

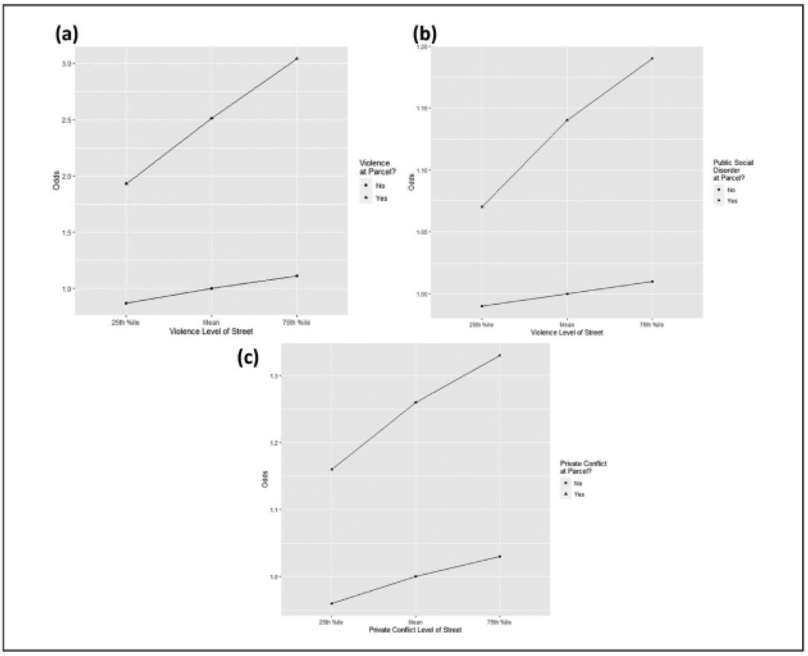

Figure 1. Odds ratios of three multilevel interaction effects, including (a) reinforced persistence of violence (binary model) between parcel (i.e., address) and street levels, (b) mediated persistence of violence across streets by public social disorder at a parcel (count model), and (c) reinforced aggravation of private conflict at address and street levels predicting violence at a parcel (binary model).
Note: Odds ratios calculated based on parameters reported in SOM.

a ceiling on the likelihood of a violent event at places that were also in high-crime or -disorder context. This is illustrated visually in the SOM.

Discussion

The analysis demonstrated that addresses (as measured with land parcels), streets, and neighborhoods (as measured with census tracts) each play substantial roles in the prevalence of violent crime over time. Critically, these roles are intertwined, as reflected in the numerous interactions between crime and disorder at different geographical scales that further shaped both persistence and aggravation of violent crime. Both types of theories for how disorder might evolve into crime—either treating crime as responding to the opportunities presented by public disorder or as an escalation from private disorder—were found to be most relevant at addresses than at streets or neighborhoods, further illuminating the distinct role played by each scale in the patterning of crime across a city.

A hierarchy emerged as to which scales "matter" for the patterning of crime, quite similar to that seen in research on concentrations of crime (O'Brien, 2019; Schnell, Braga, & Piza, 2017; Steenbeek & Weisburd, 2016). Addresses were at the forefront, accounting for half of the main effects and presenting in over 80% of the positive interaction effects. Streets were then moderately more impactful than neighborhoods, featuring more main effects and having twice as many interactions with addresses. This indicates that persistence and aggravation operate at each level, but most often through addresses and the interactions they have with their broader context.

Consistent with our hypotheses, we observed only three of the five categories from our taxonomy of cross-scale interactions. Unsurprisingly, reinforced persistence was most common, present in over half of all possible cases and notably the only type that occurred between streets and neighborhoods. The two other types of interactions were each similar to reinforced persistence in their own way: cases of mediated persistence featured continuation of violent or gun events and cases of reinforced aggravation saw a pathway from one type of crime or disorder to violence amplified by the presence of the same type of crime or disorder at a higher scale. Moderated aggravation and moderated persistence were not present at all.

Overall, these results offer a framework for better understanding how both persistence and aggravation operate across geographical scales, highlighting the complementary role of communities and places. That is to say, while the "action" appears to be strongest at addresses, streets and neighborhoods play a supporting role by influencing address-level dynamics—what we might call the "setting," or the broader backdrop against which the action unfolds. The remainder of this section explores the implications of these findings as well as potential extensions and applications of the framework for cross-scale interactions. Before doing so, we first must acknowledge limitations that will need to be remedied in future research. First, the analysis is of a single city and will need to be replicated. This is always a concern for research on crime across the urban landscape but is especially important here because of the vast number of statistical tests, even though we have taken necessary precautions around multiple tests. Second, 911 dispatches are subject to reporting biases among the public. Multiple studies have found that call hotlines have erroneous reports and unreported issues that vary systematically by neighborhood (Klinger & Bridges, 1997), though O'Brien et al. (2015) found this skew was weaker for reports regarding the deterioration and misuse of private property. We do note, however, that the 911 dataset includes officer call-ins as well as constituent-generated reports. The distribution of reports from these two sources across census neighborhoods was highly consistent for all 911-based measures[10], indicating little if any systematic difference between these two measurement strategies.

Last, we have concentrated here on neighborhoods that are primarily residential, precisely because the dynamics between disorder and crime—including the multivariate relationships and the predominant forms of persistence and aggravation —could be different in other neighborhoods, especially downtown areas. As noted above, residential neighborhoods still include a diversity of land uses, including business districts, parks, and other amenities designed for local residents, making the results here relevant to other cross-scale work focused on these non-residential places (e.g., Boessen & Hipp, 2015; Deryol et al., 2016; Taylor et al., 2019). Future work should expand on this line of inquiry.

Aggravation and Persistence: Intertwined Processes

The predominant importance of addresses for both persistence and aggravation made them the heart of the proverbial "action". For persistence, this was not necessarily surprising given the previous work identifying persistence at addresses, streets, and neighborhoods alike (Bennett, 1995; Johnson et al., 1997; O'Brien & Winship, 2017; Trickett et al., 1995). For aggravation, it was more informative, as work on the subject has historically defaulted to community-level perspectives. The results here join recent theorizing and empirical findings that point to the role of places. BWT relies on the perception and reaction to disorder, which would presumably be localized. Fittingly, Wheeler (2017) has found evidence that public disorder on a street segment is predictive of future crime there. Likewise, the theory of ecological advantages posits how disorder can enable crime at a specific location (e.g., abandoned buildings as hiding places for contraband). Meanwhile, SET's premise that private disorder is the precursor of crime within a stressful relationship or social context would also seem to be located at a rather narrow geographic scale. If the underlying conflict is isolated to a few individuals, the subsequent violent events might be expected to be confined to their private spaces. The results largely support these localized interpretations.

Focusing on the primacy of addresses alone would oversimplify the story, however, ignoring how the "setting" created by higher geographical scales shapes localized dynamics. First, the complementarity of the multiple geographical scales is most readily apparent through reinforced persistence. Figure 1a, for instance, illustrates how violence was twice as likely to occur at an address that had experienced violence in the current year than at a new address on a high-violence street. Nonetheless, address-level persistence was considerably more likely on high-violence streets, demonstrating how criminogenic factors at the two levels reinforced each other. Similarly, we see cases of reinforced aggravation, as in Figure 1c, where the prevalence of private conflict at an address and its street created the greatest risk for future violence.

The third prominent type of interaction was mediated persistence, which was notable in that it merged persistence and aggravation. Figure 1b illustrates one such case, in which violence on a street continued into the following year but was more likely at addresses that had experienced public social disorder. If we treat an address with disorder as vulnerable to future violent crime, mediated persistence shows that these vulnerabilities depend in part on a violent context. This interplay differs from traditional articulations of BWT, ecological advantages, and SET, which describe the relationship between disorder and crime as being universal. Our findings instead align with the perspective that, if disorder leads to violent crime, individuals must harbor some initial inclination toward such behavior, an assumption that is tenuous in certain contexts (O'Brien et al., 2018; Sampson, 2012). Meanwhile, such a dynamic also suggests that the persistence of violent crime throughout a street or neighborhood is most likely to manifest through addresses that are vulnerable to such events—vulnerability being indicated by the presence of other forms of crime and disorder. As such, persistence and aggravation are distinct phenomena that also are intertwined across geographical scales.

Extending and Applying the Framework

The taxonomy of cross-scale interactions is a useful tool for advancing theories of communities and crime more generally, especially if we expand the concept of "aggravation" to encompass any process that exacerbates or mitigates crime. The taxonomy also holds numerous practical applications. Turning first to extension to other theories, we illustrate with the example of informal social control as a mechanism for deterring and preventing crime. Recent work suggests that, while communities differ in their level of informal social control, its expression across the streets and institutions of a community also varies (Browning, Calder, Soller, Jackson, & Dirham, 2017; Weisburd, White, & Wooditch, 2020). The current framework could help clarify how levels of informal social control at these multiple scales combine to influence patterns of crime. One of the main findings here was how crime persists in neighborhoods through the most vulnerable places (i.e., mediated persistence). Therefore, informal social control could be an especially important protective factor for streets or institutions in high-crime neighborhoods. It is also feasible that neighborhood-level social dynamics influence the likelihood that crime will persist at a given address (e.g., Tillyer, Wilcox, & Walter, 2021), though this sort of moderated persistence would be distinct from the effects seen here for disorder. Mediated persistence might also reveal a link between the framework and existing work on land use and context (Boessen & Hipp, 2015; Deryol et al., 2016; Jones & Pridemore, 2019; Taylor et al., 2019). Just as we see here that violent crime in a neighborhood manifests itself through the most vulnerable addresses, those previous studies found that parks, liquor stores, and other "crime generators" were most likely to be problematic if other community factors put it at high risk for crime, such as concentrated disadvantage or high foot traffic. Similar reasoning and analyses might be applied to other criminogenic factors and processes, examinations that might further refine the five-part taxonomy presented here.

We might also leverage the taxonomy for practical purposes. As researchers have debated which scale of analysis matters for understanding crime, law enforcement has seen a parallel evolution. Community policing, which has become nearly ubiquitous since the 1980's (Greene, 2000; Skogan & Hartnett, 1997), has been joined by more localized strategies, including hotspot policing that targets high-crime street blocks (Braga & Bond, 2008; Braga, Papachristos, & Hureau, 2014; Ratcliffe, Taniguchi, Groff, & Wood, 2011) and even problem properties task forces that intervene at addresses that generate inordinate amounts of crime and disorder (LISC, 2015; Way, Trinh, & Wyatt, 2013). Although each of these approaches likely takes into consideration other geographic scales in practice, there are no explicit guidelines on how to do so. Such guidelines might be developed through the current framework. For instance, a community policing or hotspot policing effort would want to consider not only addresses that are already problematic but also those that might be vulnerable to further issues owing to the presence of disorder.

The framework could also be useful to predictive policing algorithms. The contents of these algorithms are not always explicit, but presumably many of them already include the multilevel interactions tested here, especially those based in machine learning models that include all combinations of parameters that improve prediction accuracy (e.g., Flaxman, Chirico, Pereira, & Loeffler, 2019). A predictive algorithm, however, is not the same thing as a policing intervention, and law enforcement officials have to decide how to use the information (Mohler et al., 2015). It is possible that departments are not informed that these cross-level interactions are contributing to the final advice provided by the model and therefore have no way of developing strategies that take the dynamics into account. The payoff would be greatly improved if the algorithm had an intellectual framework for guiding intervention, including the elements presented here.

Conclusion

Persistence and aggravation of violent crime in communities have been studied for decades. But as criminologists have come to better understand the distinct importance of addresses, streets, and neighborhoods, understanding of these processes has not kept up. The results here offer a new perspective that considers the complementary roles of these three geographic scales, captured succinctly in the contrast between “action” and “setting”. It would be hard to overstate how little we currently understand about *how* cross-scale interactions operate, thus we hope that the framework presented here will inform additional research, including replications, experimental and quasi-experimental research designs, and qualitative studies, that can unpack these phenomena and make them accessible for law enforcement and crime mitigation.

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Supplemental material

Supplemental material for this article is available online.

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Notes

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.
2. For 311, all reports were attributed to a known parcel, as constrained by the input system's usage of a street and address management (SAM) system, at the time of receipt. Those excluded lacked geographical information or had the address of City Hall as a default. For 911, parcels were immediately geocoded to the same SAM system by municipal servers until June 2014, at which point a new system was introduced and the coordinates of the 911 calls were projected into latitude and longitude and then spatially joined to land parcels in the Boston Area Research Initiative's Geographical Infrastructure (see Units of Analysis). There may of course still be errors in the determination of the nearest parcel at the time of the report, but these safeguards make us confident that few if any additional errors are introduced during data processing.
3. 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 in a 311 or 911 report.
4. An outlier analysis was used based on the interquartile range (IQR). Anything with change lower than -11.74% (i.e., Q1 – 1.5*IQR) or greater than 84.83% (i.e., Q3 + 1.5*IQR) was excluded. Note that many properties have a valuation of 0 according to assessments in all years because they are exempt from taxation from 2011 through 2016. These were not considered outliers.
5. The GI includes all parcels acknowledged by the City, regardless of the presence of a building (e.g., the land use code "Residential Lot" reflects an empty space zoned for residential). Thus, 311 and 911 reports can be attributed to parcels with and without buildings, meaning that the analysis neither omits events at locations without buildings nor incorrectly attributes them to parcels with buildings.
6. Readers will note that these numbers differ somewhat from previous studies using 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 land parcels described here, and the 2019 update transitioned to a more precise geocoding process (see O'Brien et al. 2019). Also, 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 the majority of its parcels. To maintain perfect three-level nesting,

parcels on a street segment that crossed over two or more tracts were attributed to the tract assigned to its street segment and not necessarily the tract containing the parcel.

7. The confirmatory factor analyses were based on counts of events of case types for census block groups, maximizing the extent to which case types included in a single category of events (e.g., private neglect) were co-incident at this level of geography. The logic here is not necessarily that these events correlate at street or parcel levels, but that parcels and streets contribute to the broader pattern of the neighborhood.
8. Having all interactions, including those between streets and tracts (shown by the terms ($x_{(on)klt}\ x_{(00n)klt}$)), accrue to the parcel equation is consistent with convention on the presentation of multilevel models. Arithmetically, all parameters accrue to the parcel equation.
9. All odds ratios based on the parameters reported in Appendix C: main effect of violence (binary) for the parcel = 0.92; main effect of violence (standardized) for the street = 0.11; interaction effect of the two = 0.31. Street violence's interquartile was -0.626–0.459, centered and measured in standard deviations.
10. The analyses were conducted for 2011–2013 (rs =.64 - .81). The categorization of officer call-ins was changed in 2014 when the department shifted to a new database system. After that time, most call-ins reverted to a code for officer call, rather than being labeled with a more specific case type. Nonetheless, we were able to compare the distributions of officer and constituent reports for 2011–2013.

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