Public and Private Spheres of Neighborhood Disorder: Assessing Pathways to Violence Using Large-scale Digital Records

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

Public and Private Spheres of Neighborhood Disorder:

Assessing Pathways to Violence Using Large-Scale Digital Records [*]

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[*]An earlier version of this paper was presented at the International Workshop on "Reimagining Broken Windows" in Amsterdam, October 24th, 2013, and at the annual meeting of the American Association for the Advancement of Science, Chicago, February 15th, 2014. Funding support was provided by the National Science Foundation (Grant # SMA 1338446) and the John D. and Catherine T. MacArthur Foundation (Grant # 13-105766-000). We thank the JRCD reviewers and editors along with Larry Sherman for helpful comments. We also thank Bill Oates, Curt Savoie, and the City of Boston's Department of Innovation and Technology for supporting our data access and Gabriel Cunningham for database management.

Abstract

Objectives: "Broken windows" theory is an influential model of neighborhood change but there is disagreement over whether public disorder leads to more serious crime. This paper distinguishes between public and private disorder, arguing that large-scale administrative data provide new opportunities to examine broken-windows theory and alternative models of neighborhood change.

Method: We apply an ecometric methodology to two databases from Boston: 1,000,000+ 911 dispatches; and indicators of physical disorder from 200,000+ requests for non-emergency services. Both distinguish between disorder in public and private spaces. A cross-lag longitudinal analysis was conducted using two full years of data (2011-2012).

Results: The two databases provided six dimensions of physical disorder, social disorder, and crime. Analysis of a cross-lag model revealed eight pathways by which one form of disorder or crime in 2011 predicted a significant increase in another in 2012. Although traditional interpretations of broken windows emphasize the role of public disorder, *private conflict* was the strongest predictor of future crime.

Conclusions: Our results support a *social escalation model* where future disorder and crime emerge not from public cues but from private disorder within the community, demonstrating how "big data" from administrative records, when properly measured and interpreted, represent a growing resource for studying neighborhood change.

Urban researchers and criminologists have long noted the salience of physical and social disorder in public spaces, such as litter, graffiti, loitering, and public drunkenness. Whether the 19th-century research of Booth (1889), the treatise of Wirth (1938) during the heyday of the Chicago School, Sennett's (1970) work on the "uses of disorder" in the 1970s, or Skogan's (1990) major statement on disorder near the end of the 20th century, urban disorder has been an animating concept in scholarly debates on the understanding of cities.

It was the seminal paper of Wilson and Kelling (1982), however, that launched disorder to the public stage. Writing in *The Atlantic*, they invoked the powerful metaphor of "broken windows" to capture the idea of public disorder and its hypothesized link to the unraveling of public spaces. Wilson and Kelling (1982) asserted that visual cues of disorder provoke fear among urban residents and that disorder begets predatory crime and neighborhood decline.[1] As a basic description of the urban landscape, the broken windows claim of a connection between high levels of disorder and crime has largely been supported (see especially Skogan 1990; Taub et al. 1987; Taylor 2001). Neighborhoods characterized by social and physical disorder also suffer from a variety of other maladies that are less immediately visible but still important, like poor health, high rates of school dropout, lack of trust, and public cynicism (Sampson 2012).

Where disagreement has emerged is around the meaning of disorder and the pathways by which it is—or is not—linked to crime and neighborhood decline. Traditional interpretations of broken windows theory argue that disorder precipitates a cycle of "disorder and decline," as it has been dubbed by Skogan (1986; 1990). In this model, disorder signals to others a space that is not well monitored and where crimes might be perpetrated with impunity, in turn encouraging delinquent behavior by potential offenders and inducing fear among residents, hindering the ability of the community to combat further incivilities and crime. A large body of research is ambiguous on the central claim of broken window theory—some scholars have found direct links of disorder with crime, others none, and still others a conditional relationship.[2] This work includes studies that have measured neighborhood conditions at a given time point or tracked disorder longitudinally (Fagan and Davies 2000; Markowitz et al. 2001; Perkins et al. 1993; Steenbeek and Hipp 2011; Taylor 2001) and experimental work on behavioral responses to disorder (Keizer et al. 2008; O'Brien and Wilson 2011). Another line of work has argued that disorder and crime are correlated because they both arise from common sources, such as structural disadvantage or a community's collective efficacy (Sampson and Raudenbush 1999).

Despite much research, the body of work on broken windows theory leaves open the central question: Does disorder contribute to the ongoing decline of a neighborhood? And, if so, through what behavioral and social pathways does it do so? The contribution of the present paper is to introduce a novel data source to addressing this question. As we discuss more in the next section, the advent of large administrative data sources, referred to popularly as "big data," provides for detailed assessments of various components of disorder across time and space, and hence the opportunity to track them longitudinally in relation to cycles of violence, potentially shedding new light on the predictive analytics of broken windows.

Extending Research on Broken Windows in the Age of Big Data

The "Age of Big Data" has been widely proclaimed (Anderson 2008; Boyd and Crawford 2011; Lazer et al. 2009). From cell phone and e-mail records, to weather stations and traffic sensors, we are constantly generating digital traces of attitudes, behaviors, interactions, and conditions throughout society. Nowhere is this more apparent than in cities, where there exists the greatest volume of activity to track, as well as the highest density of technology to do so.

Despite the strong claims about the potential for big data (Anderson 2008), the promised transformation to the social sciences has been slow in coming. A key challenge is that large-scale administrative data are not created for research purposes—it is not clear what they measure or how they are relevant to substantive questions. Consequently it will take effort and care to develop new methodologies that take specific data sets of interest and properly incorporate them into any science, be it criminological or otherwise. Yet, given the volume and detailed content of digital data, we believe that advances are possible. In the current case, we build on prior criminological work using calls for service to measure crime (e.g., Klinger and Bridges 1997; Sherman et al. 1989; Warner and Peirce 1993) and on methodological advances in ecometrics (Raudenbush and Sampson 1999) to develop a methodology for generating longitudinal measures of disorder. Ecometrics is increasingly used in criminological studies of surveys or observational instruments, but the models articulated by Raudenbush and Sampson (1999) were intended for researchers to construct and administer protocols for data collection that would reliably capture a particular characteristic of a neighborhood. They did not confront the task of constructing ecometrics from pre-existing administrative data. Moreover, using 311 or 911 calls to measure multiple dimensions of disorder introduces measurement issues distinct from crime.

Taking up this challenge, O'Brien, Sampson, and Winship (2015) have proposed a methodology for ecometrics in the age of digital data, identifying three main issues with such data and articulating steps for addressing each. These are: 1) identifying relevant *content*; 2) assessing *validity*; and 3) establishing criteria for *reliability*. They illustrated this approach by measuring physical disorder from over 300,000 requests for non-emergency government services received by Boston, MA's Constituent Relationship Management (CRM) system over a 2.5-year period. The first issue, *content*, arose from one of the purported strengths of digital data—they were too rich in information to be immediately useful. Distinct from the limited forms of crime (e.g., robbery, assault, burglary) that have been used in calls-for-service data, the authors identified an initial set of 178 different types of requests and then isolated 33 indicators reflecting deterioration or denigration to public spaces. Following Raudenbush and Sampson's (1999) analytic logic, further analysis produced two subfactors: *private neglect*, including housing issues (e.g., pests), the uncivil use of private space (e.g., illegal rooming houses or parking on lawns), and complaints about big buildings (i.e., condos); and *public denigration*, including requests for graffiti removal and issues regarding the improper storage or disposal of trash.

Second, O'Brien et al. (2015) noted the concern of validity for any measure based on constituent calls. Analogous to measurement error in using police calls to measure traditional index crime, if neighborhood residents systematically differ in their tendency to report issues such as graffiti or public intoxication, the resultant measures will be biased.[3] To address this issue, the authors examined independent neighborhood audits to measure a "civic response rate" that was used to calculate an adjustment factor for calibrating the call-based measures and thus better reflecting objective conditions. The adjusted measures of private neglect and public denigration correlated strongly with other indicators of blight, establishing construct validity.

Third, administrative data do not come with guidelines regarding the spatial or temporal windows at which they are most appropriately measured (Hipp 2007), meaning researchers must establish criteria for reliability themselves. O'Brien et al. (2015) assessed the reliability of both private neglect and public denigration at different time intervals and concluded that they could be reliably measured every six months for census block groups and every two months for tracts.

In sum, O'Brien et al. (2015) provided an initial demonstration of the opportunity administrative records hold for ecometrics: the database supported a multidimensional measure where protocols typically capture a single dimension, including a way to access conditions on the inside of houses, away from public view; and the authors' procedures can be replicated longitudinally with relative ease and for minimal cost, because the data are generated continuously by the city's call centers. These simple facts stand in stark contrast to the extensive time and effort associated with whole-city or community surveys and observational studies.

Strategy and Hypotheses

The current study extends the methodology of O'Brien et al. (2015) to a database of over one million 911 dispatches, adding to their measures of physical disorder a set of metrics regarding social disorder and violent crime. We then examine a longitudinal model to assess the pathways through which these various indicators of disorder and crime predict neighborhood decline.

First, we anticipate that the 911 database will generate multiple measures of social disorder (e.g., about public intoxication, disturbances) that are conceptually and statistically distinct from crime (e.g., gun violence, robbery). Second, drawing on O'Brien et al.'s (2015) distinction between public denigration and private neglect—or what might be considered "hidden" disorder that is outside of public view—we hypothesize that the 911 data document important aspects of violence that will be similarly divided between elements that are visible in public spaces and those that occur in private spaces. We focus in particular on private conflict (e.g., domestic violence) and tenant-landlord disputes.

To examine these initial hypotheses we identify case types in the 911 system that are relevant to the respective dimensions of crime and disorder and subject them to factor analysis, distinguishing our methodology from previous work that mostly focuses on behavior in public spaces or on calls about crime. With a measurement model of the dimensions of social disorder and crime in hand, we then examine the correlations between the newly constructed measures and other, external indicators, with the goal of establishing construct validity. As a last measurement step, we assess reliability characteristics for all factors.

Our intent, however, is not just to develop new ecometrics of disorder, but to leverage them for the substantive study of the dynamic relationship between broken windows and crime. To this end, our final set of analyses focus on longitudinal prediction models that combine metrics from the 911 and CRM databases with other relevant measures of the demographic and social structure of the neighborhoods, asking whether and how disorder and crime reinforce each other in an ongoing cycle of neighborhood decline. This question is critical, because policing strategy has increasingly and explicitly moved to predictive analytics. Indeed, strong claims have been made for the ability of police departments to predict future crimes based on the location and type of prior crimes (http://www.predpol.com/), and we know that "hot spot" analysis of crime events has informed policies on the allocation of patrols (Weisburd et al. 2012). *But how do indicators of broken windows fare in the prediction of future crime?* According to the signaling mechanism central to broken windows theory, public or visible cues of disorder should have independent predictive power beyond that of crime itself. We test this hypothesis directly. In addition, we examine if and how the hypothesized elements of violence and disorder that are private or hidden in nature are predictive of future levels of public disorder and crime, potentially presenting alternative pathways of neighborhood decline.

To summarize: we first develop a measurement model and then test whether and how our derived measures of physical disorder, social disorder, and private conflict predict future neighborhood disorder and violence, controlling for relevant factors such as neighborhood demography and collective efficacy. Given the prominent place that visible forms of public disorder hold in broken windows theory, in that they offend ordinary citizens and draw potential offenders from outside the community, we pay specific attention to the ability of public cues of disorder to predict increases in future disorder and crime. We also assess the ability of private disorder to predict future disorder and crime, a question that while theoretically important, has been far less studied. Finally, we go beyond the interpretation of discrete cross-time effects and emphasize their composite, looking for evidence of longer-term trajectories or feedback loops that would indicate pathways for the unraveling of a neighborhood. Overall, we view our analyses as both an examination of broken windows theory and a further step towards incorporating the use of large-scale administrative data in criminology.

Data and Measures

The current study focuses on a window spanning the years 2011 and 2012. In this period, Boston generated 1,165,264 911 dispatches (1,022,150 with geographic reference) categorized into 381 different case types. Case types, intended to capture the nature of the emergency, were determined from a standardized list at time of dispatch. A subset of types reflected instances of social disorder (e.g., disturbance, public intoxication) and crime (e.g., robbery, shooting). Other case types were less relevant (e.g., cardiac arrest). Each case record included the date of the dispatch and the address or intersection where services were required. Cases were attributed to the appropriate census geographies (both block groups (CBGs) and tracts; from the 2005-2009 American Community Survey, the most recent census with socioeconomic data when the database was built), which we used to approximate neighborhoods. The main measures for analysis were rates of events (per 1,000 inhabitants).

The longitudinal analysis and validation utilized neighborhood-level measures drawn from four other databases:

1) Homicide records were provided by the Boston Police Department (N = 113 events in 2011-2012). Because of their overall rarity, counts were used instead of rates.

2) The CRM system was used to measure the two aspects of physical disorder, private neglect and public denigration drawn from a database of 281,921 requests for service in 2011-2012. Private neglect was comprised of cases that captured 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). Public denigration was comprised of cases reflecting graffiti and the improper disposal of trash. Neighborhood-level measures were calculated in two steps. First, counts of all events in each category were tabulated. Second, they were adjusted using the neighborhood's estimated civic response rate, which was based on the proportion of residents who had a registered account with the system and had made at least one call referencing a public issue (versus only using it for personal needs, like requesting a bulk-item pickup; see O'Brien et al. 2015).

3) Demographic measures, including median income and ethnic composition, were accessed from the census' American Community Survey (2005-2009 estimates).

4) The Boston Neighborhood Survey (BNS) provided a measure of collective efficacy (i.e., cohesion between neighbors and their ability to enforce local social norms). The BNS was a telephone survey that recruited participants by random-digit dial. Here we use the 2010 wave (N = 1718). Its content and methodology was modeled after the community surveys designed by

the Project on Human Development in Chicago Neighborhoods (Sampson 2012: 83-84). Collective efficacy was calculated as an aggregate of residents' responses, controlling for individual-level demographic characteristics (gender, age, ethnicity, and parental status).

Measurement Model for Social Disorder and Crime

We first identified 41 case types reflecting social disorder or crime. Neighborhood-level rates for each were calculated for a single calendar year (2011), based on the intention to use this as the temporal unit of measurement throughout. These were examined using exploratory factor analysis, with CBGs as the unit of analysis (in order to permit sufficient sample size; $N = 542$). In this process, 20 of the case types were removed for one of three reasons: 1) they were too infrequent to be meaningful (e.g., carjacking); 2) they failed to load on any factor; 3) they were too general and had a strong relationship with every factor (e.g., disturbance). Two others that both indicated that a person had been shot were combined.

The analysis of the remaining 20 items suggested five factors. Each captured a particular theme, but some also included one or more items whose content was not entirely consistent with the others. This result is to be expected because of the various potential pathways of shared or mutual causation that might exist between different types of disorder and crime. We modified the factors to reflect five internally consistent and theoretically appropriate measures:

- *Public Social Disorder*, such as panhandlers, drunks, and loud disturbances.
- *Public Violence* that did not involve a gun (e.g., fight).
- *Private Conflict* arising from personal relationships (e.g., domestic violence).
- *Prevalence of Guns Violence*, as indicated by shootings or other incidents involving guns.
- *Alcohol*, including public drunkenness or public consumption of alcohol.

Alcohol shared many items with *public social disorder* and its unique variance was concentrated in regions with many bars in the downtown region; overall, it was not relevant citywide. For this reason, a final confirmatory factor analysis examined only the first four factors, showing good fit (items and loadings in Table 1; CFI = .94, TLI = .91, SRMR = .05).[4]

Table 1 about here

To establish construct validity, we examined the correlations between these four measures and other indicators of blight from the CRM database, the Boston Neighborhood Survey, and the American Community Survey. From here on, in order to position our results to be maximally comparable to other studies, we analyze at the more traditional level of census tracts. In addition, we limit to residential areas (N = 121 tracts), excluding downtown and institutional regions (e.g., college campuses), because these areas generate idiosyncratic patterns and few community surveys. The correlations between the four measures derived from 911 dispatches and the other indicators of blight were as theoretically expected (see Table 2). In particular, guns, private conflict, and public violence were strongly associated with lower median income, higher proportion Black, and lower collective efficacy (magnitude of r's = .27 - .81, all p-values < .01). Additionally, these measures were associated with physical disorder, including strong correlations with private neglect (r's = .54 - .71, all p-values < .001), and moderate correlations with public denigration (r's = .27 - .36, all p-values < .01). Public social disorder had a somewhat different profile, featuring lower correlations with contextual characteristics (magnitude of r's = .10 - .30, two of four p-values < .05) and private neglect ($r = .15$, $p < .10$), but one of the stronger correlations with public denigration ($r = .33$, $p < .001$).

Table 2 about here

As a final step, we examined the reliability of the four measures at the neighborhood level by splitting up the two-year database into equal intervals and evaluating the consistency between measures of the same neighborhood relative to the overall variation. We performed this test iteratively, varying the size of the time window in order to identify the smallest interval that achieved a sufficient level of within-neighborhood consistency. All four measures achieved moderate to high intra-neighborhood consistency for four-month windows (intraclass correlation coefficients > .75). In addition, neighborhoods could be reliably differentiated from each other in each model (all λs > .85), indicating that any larger window of aggregation will be able to provide reliable measures—including the year-long windows we use in the proceeding analysis.

Longitudinal Results

We used structural equation models to evaluate cross-time or "cross-lag" relationships (Kenny 2005) between the two measures of physical disorder from the CRM data and the four measures of social disorder and crime from the 911 dispatch data. Again, we limited the analysis to census tracts that are primarily residential (final N = 121). The model had three layers. First, the 2011 measures were regressed upon important contextual factors that prior research tells us influence levels of disorder and crime: median income, percentage Black, percentage Hispanic, and collective efficacy. The 2012 measures were then regressed upon all of the 2011 measures, as well as the four control measures. Last, the model was trimmed to only include significant predictors, producing a final model with strong fit (CFI = .98, TLI = .97, SRMR = .06). Given our substantive interests here, we only report three classes of parameters from the model: 1) measures of disorder and crime in 2011 predicting the corresponding measure in 2012; 2) measures of disorder and crime in 2011 predicting other measures of disorder and crime in 2012; and 3) error covariances between measures of disorder and crime from the same year.[5]

Table 3 about here

We center our discussion on the second of these three classes, as these are reflective of cycles of disorder and decline. Eight such parameters emerged (excluding the homicide path, to be discussed), depicted schematically in Figure 1. In four of these eight, the predictive measure was private conflict in 2011. In order of effect size, private conflict was associated with increases in public social disorder (B = .33, $p < .001$), guns (B = .19, $p < .05$), public violence (B = .17, $p < .01$), and private neglect (B = .15, $p < .05$). Reciprocally, guns in 2011 predicted elevated levels of private conflict in 2012 (B = .33, $p < .001$). Public violence in 2011 had two cross-time patterns, predicting increases in guns (B = .20, $p < .01$) and public social disorder (B = .22, $p < .10$). Last, public social disorder predicted increases in public violence (B = .11, $p < .01$), but this estimate was the smallest in the cross-time models. Notably, the measures of physical disorder in 2011 did not predict changes in any of the other measures across time.

Figure 1 about here

As a last step, we expanded the analysis to include counts of homicides using a zero-inflated Poisson distribution. Two sets of parameters were estimated: whether a tract had any homicides; and, if there was at least one homicide, how many occurred. Significant predictors emerged only for counts, with guns in 2011 predicting more homicides in 2012 (odds ratio = 1.06, $p < .01$), controlling for homicides in 2011 (odds ratio = 0.26, $p < .05$). Notably, the prevalence of guns was a stronger predictor than the assumption of stability in homicide counts across time. Homicides in 2011 did not predict any other measures of disorder or crime in 2012.

Implications of Using Big Data to Study Neighborhood Change

Criminologists and others studying urban neighborhoods have long theorized about the dynamic processes responsible for neighborhood change and stability, but the challenge of testing such hypotheses longitudinally has thwarted empirical progress. The current study has demonstrated one way that large-scale administrative data might be leveraged in this effort; taking an ecometric approach we translated over one million records of calls in Boston into a diverse set of measures spanning physical disorder, social disorder, and crime. The data are continuous, supporting measurement at various time intervals and spatial scales, and they provide multiple measures of disorder and crime that can be reliably and validly analyzed with cross-time models.

To our knowledge, this is the first study in which large-scale administrative records—a form of big data—were systematically joined with ecometrics to study the dynamics of broken windows theory. The measures of social disorder and crime generated by the 911 dispatch data highlighted the advantages of 311 call data in a manner extending O'Brien et al.'s (2015) initial ecometric work with Boston's CRM data. Not only did the measurement model uncover multiple dimensions, it also distinguished between incivilities in public versus private spaces—demonstrating how call records can "see" things in private that would be difficult to measure using neighborhood audits or other traditional methodologies. Further, the ability afforded by the data to test a broad set of cross-time relationships highlighted the possibility that the unraveling of a neighborhood is not the product of any single mechanism, but of multiple concurrent mechanisms that drive change.

The same characteristics that enabled this study make the data potentially useful to other questions surrounding the study of disorder and crime. Their specificity could support microspatial analyses of hotspots (Braga et al. 2010; Braga et al. 2011); the continuous data streams could track outcomes in future policing experiments and other neighborhood interventions; and the calls themselves might even be used as indicators of the care and responsibility individuals take for the public space (O'Brien 2014). Thus, as noted at the outset, our study is a first step, one intended to set the groundwork for continued efforts to leverage administrative data in the study of neighborhood dynamics.

There are nonetheless several limitations and qualifications to our study that we wish to address. The first qualification is that the utilization of large-scale digital data to study crime and disorder is intended to complement existing approaches, not replace them. For this reason, we have argued that this study is meant to both assess broken windows theory and broaden its empirical basis, contributing to a future research agenda using new indicators of disorder. We would emphasize that the possibilities go well beyond call data. For example, visual data on disorder are now available on streets around the world in Google Street View, and methods have recently been developed to systematically and reliably code them (Hwang and Sampson 2014).

Second, we were only able to incorporate two time points of disorder and crime, limiting the patterns that we can observe. If there are dynamic relationships between disorder and crime that operate at a temporal scale greater than a single year, they are not captured in our data. Third, our primary focus on the interactions between disorder and crime has set aside the roles of structural disadvantage and collective efficacy, something that should be explored in future work. We controlled for their effects, in other words, but did not probe the pattern of results.

Fourth, although measurement error was modeled and cross-lag models provide an advantage in assessing neighborhood change, we do not claim to have rigorously identified causation, especially given the possibility of unobserved covariates or the existence of different causal lags (Singer and Willett 2003). However, it is important to reemphasize that a major issue of concern in broken-windows theory is precisely longitudinal predictions over time. Even if we have not demonstrated causality, longitudinal patterns that run in opposite directions from the theory are crucial. Indeed, that private conflict turned out to be the major predictor of public violence, which in turn was more predictive of public disorder than the reverse, is informative for assessing the predictions of the theory and for predictive analytics in crime policy.[6]

Finally, our analysis describes a single city at a single time, and a robust evaluation would require replications with additional time points and locales. In this regard, we would note that in addition to the need for replication in other cities, methods such as ours are dependent on cities that have good systems for fielding and analyzing calls for service. In cities like Boston where government capacity and administration is strong, this is not a problem—in fact Boston boasts an "Office of New Urban Mechanics" that is devoted to the quality of open city data. But no doubt many cities do not have the capacity or the motivation to instate such systems, and thus are not soliciting and compiling information about social or physical problems. The use of call data also assumes consistency in decision rules for recording and retaining calls. As administrative data continues to grow in popularity and sophistication, long-term studies and multi-city comparisons will become increasingly possible and create new opportunities to address these measurement issues.

Theoretical Synthesis and Implications

Within the limitations of our data, our results provide insights about the dynamic predictions of broken windows theory. The longitudinal results identified eight different cross-time relationships between aspects of physical disorder, social disorder, and crime, and nearly all measures were involved as either predictors or outcomes. Although we only have two time points and we make no claims to having demonstrated causality, the findings bear on how a neighborhood might gradually unravel. As denoted in Figure 1, one pathway is from milder to more serious incivilities and crimes, running from public social disorder to public violence to the prevalence of guns all the way to homicides. This incremental progression is consistent with how broken windows theory is traditionally described.

There were also feedback loops implied by the results. One was limited to public spaces, where social disorder and violence appear to share a reciprocal effect. Another loop seemed rooted in personal relationships, as private conflict and guns reinforced each other across time. Recent research supports one of part this dynamic, with rates of gun ownership strongly predictive of nonstranger homicide rates but not stranger homicide rates (Siegel et al. 2014). The feedback loop implicated in our model suggests that private disorder spills into the public space, which then increases the intensity of conflict in private spaces, if one follows the pathway from private conflict to public violence to guns and then back.

At first blush these patterns seem consistent with a traditional interpretation of broken windows theory, whereby incivilities create a context that enables or encourages more serious issues. The specific relationships did not follow classical formulations of the theory, however, which tend to emphasize the role of disorder in the *public* sphere, primarily as a suite of visible cues that either encourage further incivility or erode communitarian behavior (Skogan 1990; Taylor 2001; Wilson and Kelling 1982). This signaling model has been embodied in broken windows policing initiatives that crack down on public incivilities (Braga and Bond 2008; Harcourt and Ludwig 2006); it has also been the basis of experimental and survey research on the behavioral impacts of visible disorder (e.g., Drakulich 2013; O'Brien and Wilson 2011; Ross and Mirowsky 2001; Theall et al. 2013). For signaling to be the predominant explanatory mechanism, public denigration to physical spaces and public social disorder should be prominent in predicting cross-time relationships. This was not the case: public denigration had no predictive power, belying the role of literal broken windows; and the link from public social disorder to later public violence was half the magnitude of the reverse pathway from violence to social disorder. Put more simply, both physical and social forms of public disorder were weakly predictive of future violence and disorder, if at all.

Perhaps most interesting, *private* conflict was the strongest leading indicator in the model, predicting increases in public social disorder, public violence, guns, and even physical disorder in privately owned spaces. These links in the model appear to suggest an alternative pathway to neighborhood violence, one we term the "social escalation" model, wherein the persistence and expansion of disorder and crime percolate outward from the neighborhood's social ecology. Private conflicts, for example domestic violence or friendship disputes over money or girlfriends, can and do spill over into public spaces, be it on front stoops or street corners, in bars or local parks. Likewise, both private conflict and public violence are likely to increase in severity over time, leading to the more consistent use of guns. Notably this progression has been largely invisible to previous work because its primary antecedents occur behind closed doors, out of view of many measurement techniques.

Integrating Social Escalation and Disorder Theory

Our analysis provides a new set of information and hypothesized mechanisms by which disorder and violence precipitate community change. One mechanism, which has already been described, is that private conflict manifests itself repeatedly, in different contexts or at new levels, reinforcing itself over time. But this cycle of violence almost certainly is not the complete story, as it would assume that the same interpersonal relationships and individuals that create private conflict are responsible for the increases in other aspects of disorder and crime.

An alternative mechanism, which is not mutually exclusive, is that the initial levels of disorder and crime have an indirect effect, creating a context within which new issues are able to emerge. There is precedent for this approach in the original model of broken windows, as one of the proposed pathways was that the fear induced by disorder would cause people to remove themselves from the public sphere, in turn diminishing social ties and trust in the community (Perkins et al. 1993; Skogan 1990; Wilson and Kelling 1982). Consequently, the community would be unable to manage public spaces, and increased disorder and crime would follow.

We were unable to measure social control at two different time points in the present study and so this model could not be directly tested, but it has been reported by other researchers. Using the British Crime Survey, Markowitz et al. (2001) found that both disorder and burglary predicted lower cohesion at later time points. In a study of ten years of data from Utrecht, Steenbeek and Hipp (2011) reported a negative impact of disorder on the community's perceived potential for social control across time. This mediational model, with disorder first diminishing control, could provide an indirect pathway for some of the findings seen here. For example, individuals who fight in public might not be the panhandlers and drunks that create public social disorder in the future, but they may clear the space of more positive influences.

An important consideration for either of these interpretations is the individual-level process or processes that mediate these relationships. In the signaling model, it is the information communicated by incivilities that suggests to others the opportunity to do likewise. To better understand the social escalation model, we turn to another literature looking at the mental health consequences of disorder. One of the most consistent results in this work is that disorder elevates stress levels, leading to a variety of other sequelae, such as altered cortisol levels (Dulin-Keita et al. 2012) or shortened telomeres in a person's DNA (Theall et al. 2013), both of which are important biomarkers of the amount of stress a person regularly experiences. Other studies have found that the perception of higher disorder in a neighborhood can lead to a sense of powerlessness and lack of trust (Ross and Mirowsky 2001; Ross et al. 2001), lower self-esteem (Haney 2007), and depression (Brown and Bentley 1993). When analyzing the Moving to Opportunity (MTO) experiment, Ludwig et al. (2012) observed improvements in physical and mental health associated with moving out of poor, high-crime, disorderly areas. Though many of these studies point to community disorder in a general sense, only one study, to our knowledge, has further specified the causal mechanism driving these effects. Casciano and Massey (2012) used a quasi-experimental housing program (similar to MTO) to evaluate neighborhood effects on anxiety. They found that those who moved out of high-poverty neighborhoods and into a mixed-income housing project experienced both less disorder and less anxiety. The ameliorative effect of the new neighborhood, however, was explained specifically by a diminishment in personally stressful life events, as opposed to changes to the overall ambient environment.

In short, we theorize that a stressful social ecology like that reflected in the private conflict measure might drive the behaviors of residents in a variety of ways, creating multiple consequences for the neighborhood as a whole. People experiencing elevated stress might be more likely to come into conflict, and this conflict could be more likely to erupt in violence. Those under greater stress might also allow physical spaces to deteriorate further or be less likely to take action on public social disorder. In turn, disorder as a generator of stress could potentially contribute to either direct or indirect forms of social escalation that are in turn a pathway to further neighborhood decline. If the results of our study are any guide, the dynamics of social escalation and disorder thus merit future testing.

Notes

[1] The origins of broken windows theory is sometimes traced to the famous Zimbardo study from the 1960s, which placed an abandoned car a poor/working class neighborhood in the Bronx and one in a more affluent neighborhood in Palo Alto. As reported in Zimbardo (2007), the car in the Bronx was quickly pillaged whereas in Palo Alto the car sat untouched until Zimbardo and colleagues started smashing windows. As Sampson (2013: 17) argues, the interpretation drawn by Wilson and Kelling of the Zimbardo experiment is contrary to the idea that one broken window inevitably begets another, "[C]ontext was everything even at the dawn of broken windows theory—the same cue of disorder, primed by design to be identical, nonetheless triggered vastly different responses depending on the neighborhood."

[2] We set aside a detailed review of broken windows theory and research; see Skogan (2015) and Welsh et al. (2015) for an overview. We also set aside the specific societal implications of "broken windows policing." As Braga et al. (2013) observe, there is no consensus on what broken-windows policing means, and much of the experimental research relies on the random assignment of arrest strategies to crime "hot spots" (Braga and Bond 2008), where the mechanism in question is the behavior of law enforcement, not disorder.

[3] For an excellent discussion of measurement issues and validity in measuring index crimes from call data, see Klinger and Bridges (1997) and Warner and Pierce (1993).

[4] By comparison, a single-factor model (maintaining all additional covariances between items in order to maintain equivalence) did not fit the data as well as the four factor model CFI = .76; TLI= .72; SRMR = .11).

[5] Although error covariances and contextual census-based factors are included in the model, we do not present or discuss the specific parameters. While the findings largely conform to prior research, they also deviate on a number of points, meriting more attention than space limitations allow us here. We are therefore exploring this issue in another paper. Our goal here is simply to control for major neighborhood correlates of crime in assessing pathways of disorder.

[6] We would note as well that the limitation on causal inference arising from potential unobserved covariates applies to all observational data. Experiments solve this problem but face equally serious external validity limitations, and moreover, existing experiments in criminology do not address the neighborhood-level mechanisms at issue in this paper.

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Table 1. Case types included in the final four-factor model of social disorder and crime, including loading on factor and frequency in 2011.

Case Type	**Count (2011)**	**Factor Loading**	**Case Type**	**Count (2011)**	**Factor Loading**
Public Social Disorder			*Private Conflict*		
Intoxication: Individual	1148	.76	Domestic Violence Intimate/Partner	5151	.89
Drunks Causing Disturbance	916	.81	Landlord/Tenant Trouble	668	.52
Panhandler	673	.59	Vandalism Report	3673	.61
Sex Offense/Lewd Behavior	787	.55	Violent Restraining Order	997	.61
Vandalism in Progress	805	.62			
Public Violence			*Prevalence of Guns*		
Assault and Battery in Progress	2793	.87	Assault and Battery with Deadly Weapon	116	.42
Assault and Battery Report	1651	.68	Person with a Gun	776	.83
Armed Robbery	409	.56	Shots	854	.68
Emotionally Disturbed Person: Violent or Injured	6169	.61	Person Shot	491	.59
Fight	5906	.97			
Person with Knife	823	.68			

Note: N = 542 census block groups, using only data from 2011.

Table 2. Descriptive statistics for and correlations between measures of disorder and crime and related contextual factors.

	Public Social Disorder	*Public Violence*	*Private Conflict*	*Guns*	*Private Neglect*	*Public Denig-ration*	*Median Income*	*% Black*	*% Hispanic*	*Coll-ective Efficacy*	*Homi-cides*
Public Social Disorder[a,b]	—	.71***	.37***	.36***	.15^{+}	.33***	-.28**	.10	.13	-.30***	.15^{+}
Public Violence[a,b]		—	.79***	.79***	.54***	.36***	-.61***	.58***	.29**	-.45***	.34***
Private Conflict[a,b]			—	.86***	.71***	.28**	-.63***	.76***	.30***	-.34***	.40***
Guns[a,b]				—	.67***	.27**	-.63***	.81***	.27**	-.33***	.44***
Private Neglect[b]					—	.49***	-.64***	.67***	.32***	-.39***	.33***
Public Denigration[b]						—	-.39***	-.08	.36***	-.54***	.07
Median Income							—	-.56***	-.53***	.51***	-.38***
% Black[a]								—	.13	-.20*	.40***
% Hispanic[a]									—	-.37***	.11
Collective Efficacy										—	-.14
Homicides[a]											—
Mean (SD)	-0.29 (1.78)	-0.13 (3.16)	0.29 (2.36)	0.23 (2.29)	0.08 (0.57)	-0.04 (0.27)	\$53,927 (\$22,914)	0.26 (0.28)	0.17 (0.15)	7.65 (0.31)	0.438 (0.79)
Range	-2.39 – 9.84	-4.63 – 9.90	-2.59 – 7.26	-1.94 – 9.44	-1.65 – 1.19	-0.77 – 0.73	\$16,423 – \$143,819	0 – 0.91	0 – 0.62	6.83 – 8.33	0 – 4[c]

$^{+}$ - $p < .10$, * - $p < .05$, ** - $p < .01$, *** - $p < .001$ Note: N = 121 residential census tracts.
[a] – Log-transformed before correlations to account for skewed distribution. [b] – Standardized variable with global mean set to 0.
[c] – 85 (70%) had no homicides in 2011.

Table 3. Complete parameter estimates from structural equation model testing cross-time relationships between measures of disorder and crime, accounting for contextual factors.

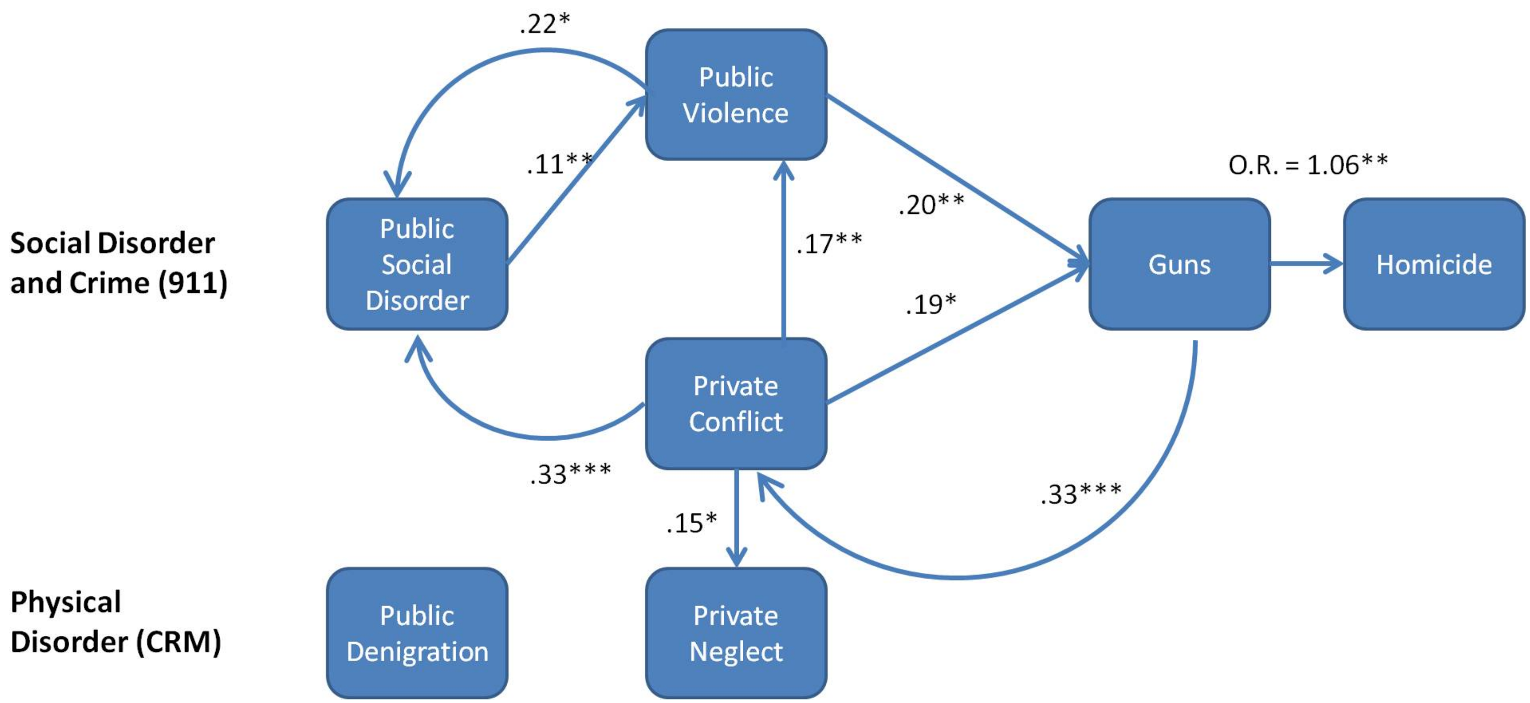
Effect	Estimate	Effect	Estimate
Stability (2011→2012)		*Cross-Time Effects (2011→2012)*	
Private Neglect	.76***	Private Conflict → Private Neglect	.15*
Public Denigration	.63***	Public Violence → Public Social Disorder	.22*
Public Social Disorder	.55***	Private Conflict → Public Social Disorder	.33***
Public Violence	.63***	Public Social Disorder → Public Violence	.11**
Private Conflict	.61***	Private Conflict → Public Violence	.17**
Guns	.41***	Guns → Private Conflict	.33***
		Public Violence → Guns	.20**
		Private Conflict → Guns	.19*
Covariances (Single Time Point)			
Private Neglect ↔ Public Denigration (2011)	.44***	Public Social Disorder ↔ Public Violence (2012)	.33***
Private Neglect ↔ Private Conflict (2011)	.19**	Public Violence ↔ Private Conflict (2011)	.59***
Private Neglect ↔ Public Denigration (2012)	.26**	Public Violence ↔ Guns (2011)	.61***
Public Social Disorder ↔ Private Conflict (2011)	.43***	Public Violence ↔ Private Conflict (2012)	.19*
Public Social Disorder ↔ Public Violence (2011)	.78***	Private Conflict ↔ Guns (2011)	.56***
Public Social Disorder ↔ Guns (2011)	.42***	Private Conflict ↔ Guns (2012)	.18^{+}

$^{+}$ - $p < .10$, * - $p < .05$, ** - $p < .01$, *** - $p < .001$

Model fit statistics: CFI = .98, TLI = .97, SRMR = .06.

Note: $N = 121$ residential census tracts. Model includes baseline controls for median income, racial composition, and collective efficacy predicting both 2011 and 2012 measures.

Figure 1. Cycles of disorder and violence: Schematic depicting significant cross-time parameters (2011→2012) from structural equation models, with baseline controls for median income, racial composition, and collective efficacy.



Note: Based on the structural equation models described in text and Table 3. $N = 121$ residential census tracts.